Mining Optimization Laboratory

Report Eight –2016/2017

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Pourrahimian, Y., Ben-Awuah E., and Askari-Nasab, H. (2017), Mining Optimization Laboratory (MOL) – Report Eight, © MOL, University of Alberta, Edmonton, Canada, 310 Pages, ISBN: 978-1-55195-383-0.

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Executive Summary

This year, we have prepared a report including 19 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 Eight (2016/2017) by considering some of the main contributors.

In paper 101, ***Mohammad*** presents a mathematical formulation that uses aggregated units for making mining, processing and stockpiling decisions while respecting various mining and processing constraints. First, he proposes a non-linear model that estimates stockpile grade and controls the head grade of material sent to the processing plants. Next, he uses the idea of piecewise linearization to modify the model to be able to solve it with mixed integer linear programming solvers. Afterwards, he shows how the model compares against other linear stockpiling models in the literature. Finally, the model is tested on a small dataset with various numbers of stockpiles to evaluate the performance of the model and show the errors introduced by linearization.

Ali and ***Shiv*** developed a multi-objective multi-stage mining fleet management system. The developed management system is responsible for semi-dynamic and dynamic decisions to be made in a mining operation. The system, in its so called upper stage, links semi-dynamic operational decision-making process to the short-term production plan by simultaneously assigning shovels to mining faces and allocating trucks to the shovels implementing its first multi objective decision-making model. Then in its second stage, in a real time dynamic decision-making process, it decides on the next destination of trucks asking for new assignment by optimizing its second multi objective decision-making model. The developed fleet management system had been verified using an Iron ore case study and the results are presented in paper 102.

Navid presents the incorporation of stockpiling and cut-off grade optimization into oil sands production and dyke material planning in paper 104. The objectives are to: 1) determine the life of mine optimum cut-off grade profile and corresponding ore tonnages to maximize the NPV of the operation; 2) determine the dyke material schedule for dyke construction; and 3) assess the impact of stockpiling and stockpile reclamation with limited duration. An Integrated Cut-Off Grade Optimization (ICOGO) model and a Mixed Integer Linear Goal Programming (MILGP) model was developed to generate an optimum cut-off grade policy and a schedule for mining ore and waste, as well as overburden, interburden and tailings coarse sand dyke materials in long-term production planning. The models were applied to an oil sands case study to maximize the NPV of the operation. In comparison, whereas the ICOGO model solved the optimization problem faster, the MILGP model results provided detailed mining-cut extraction sequencing for practical mining. In paper 202, Navid also presents an economic evaluation of a primary haulage system for a Bauxite mine. A haulage cost analysis was conducted by comparing the capital, replacement and operational costs of a load and haul system with an in-pit crushing and conveying system.

Ali presents a truck dispatching decision-making model in paper 201. The developed model is responsible to make dynamic decisions regarding trucks next destination. The developed model has three major advantages compared to currently available models. Firstly, it optimizes all the required objectives at the dynamic decision-making level, simultaneously. Secondly, the model follows the goals of strategic planning levels and minimizes the deviation from those goals by linking the dynamic assignment stage to the production optimization stage. And, thirdly, there is no limitation regarding number of trucks to be assigned each time the model is run. To evaluate the developed model, a general reusable discrete-event simulation tool is developed and verified to analyze the behavior of open pit mining operations. The simulation tool imitates the truck-shovel operation and its interaction with the mining fleet management systems. The simulation model is linked to the mine production schedule. The developed simulation tool accurately monitors the system's major KPIs. The simulation model is run for a predetermined number of replications over the desired planning time horizon to generate tight half-widths around the monthly and shift-based KPIs with high confidence level.

Bright has been conducting a literature review on models and algorithm for strategic mining options optimization in paper 105. Current tools and methodologies used in the mining industry are not adequate in dealing with the complexity of subjecting a deposit to rigorous mining options optimization with a measure of optimality. His research focuses on the development of a well-integrated strategy for open pit and/or underground mining and their interactions. Extensive literature review and gap analysis matrix are used to identify the associated limitations. Opportunities for improving the existing models and algorithms have been proposed. In paper 103, Bright also presents the strategic evaluation of mineralized waste rocks as future resource. Current mining practices do not extract all mineralized rocks due to the present mine planning concept of economic resource depletion as opposed to physical resource depletion. Improvement in factors including mineral prices and processing recovery could potentially make mineralized waste rocks profitable. The paper proposes a framework that maximizes the benefits of mining and processing mineralized waste rocks.

Ahlam has developed a mixed integer linear goal programming (MILGP) framework to determine the production schedule simultaneously with dyke construction schedule in oil sands mining. A limited duration stockpiling strategy is incorporated for the ore material that exceeds the processing capacity in each period. Robust constraints for managing tonnage fluctuations are introduced. Kriging estimates with a variance penalty scheme are used for mine planning to minimize the risk from grade uncertainty. The topmost layer of the overburden, known as muskeg is stockpiled to be used for land reclamation at the end of mine life. The model implementation and verification with an oil sands dataset is currently ongoing.

Eduardo has been working in the area of mine optimization and simulation in the oil sands. His latest study investigated potential improvements on established methods for mine productivity analysis. Initially, in order to reduce the variance in the productivity performance indicators, he conducted extensive historical data analysis and data classification. With the variance in the results reduced, but still high, it was theorized that a more detailed study of the truck/shovel activities was necessary. The code was developed in order to digitize road networks and subsequently estimate travel times from specific shovel sources to dump destinations, in accordance with the mine plan. This introduced the concept of EFH (Equivalent Flat Haul) as a controlling parameter. This new parameter took into account the effects of gradients and changing road conditions had on the equipment utilization. The new approach incorporates simulation to provide more accurate predictions for long-range production planning and, in turn, equipment selection forecasting. In paper 203, his latest insights and results are presented.

Firouz has been carrying out research on block-cave production scheduling using mathematical programming (papers 302, 304, and 307). He looks at production scheduling problem from different perspectives such as profitability and practicality while considering the uncertainties which are involved in the operations. His model captures the grade uncertainty resulted from of the flow of material, as one of the main sources of uncertainties in block caving, using stochastic optimization. The uncertainties should be considered within the production schedule; otherwise, the resulted production schedule could be far from the real operations. The proposed model maximizes the net present value of the mining project while minimizing the production grade deviations from target grades. Through his model, a number of scenarios are considered to capture the material flow uncertainties. Testing the model for a real case block-cave mining operation shows that the proposed model can take the material flow uncertainties into the production schedule in order to achieve more reliable plans; the optimum production schedule is accomplished based on different scenarios which can happen in the real operations. The model also calculates the optimum height of draw as part of the optimization.

Farshad has been carrying out research on block-cave production scheduling using mathematical programming (papers 301, 303, and 304). He has developed a mixed-integer linear programming (MILP) model to optimize the extraction sequence of drawpoints over multiple time horizons of block cave mines with respect to the draw control systems. In paper 301, he has formulated four draw rate strategies to guarantee practical solutions. In paper 303, This paper a practical draw control system based on some conditional approaches to manage draw rates of block-cave operations is presented. The model maximizes the NPV subject to all operational and geotechnical constraints. To manage drawpoint production, a draw rate constraint based on the PRC has been established. Three different resolutions' responses to conditional constraints are added to the exact management system of PRC to control the depletion rate among all drawpoints in the caved area. In addition, he has developed a multi-similarity index clustering technique to solve the presented MILP models in a reasonable time. Multi-similarity indices aggregate the draw columns into clusters based on center-by-center distance, grade distribution, maximum draw rate according to PRC, and advancement direction. The draw column multi-similarity indices are used to (i) generate a practical mining schedule that follows a selective mining unit, (ii) reduce the number of variables, and (iii) remove the similarity index dependency for the weight factors that are defining by the planner.

Zeinab has been working towards the development of a methodology to determine the optimal underground stope layout (paper 308). The main goal of the study is to develop a framework to find the best combination of the stops with highest economic value. In fact, this research directly contributes to creating a new heuristic model which can tackle the complexity of stope layout designing and at the same time can achieve to the near-exact solution in 3D space.

Efrain presents a methodology based on Sequential Gaussian Simulation (SGS) to obtain the optimum drawpoint spacing in paper 306. The optimized drawpoint spacing is used to maximize the profit since the extraction layout is highly essential for the economics of block caving. This study is opening a new horizon for using "All Realizations All the Time" as a new approach to solve one of the trickiest elements of blocks caving.

David has investigated the effect of chemical suppressants for the control of fugitive dust emission on mine haul roads. In paper 403, he presents the role of different atmosphere temperatures on the effectiveness of chemical suppressants. In this study, water and selected chemical surfactants— salt, chloride free agents, polymers, and molasses—were tested experimentally for their dust retention efficiency under atmosphere temperatures of 35 ^{o}C (hot), 15 ^{o}C (normal), and -19 ^{o}C (cold), respectively. A large-scale wildfire had broken out at Fort McMurray in Alberta, Canada during May 2016. Many oil sands mining activities were affected due to the wildfire and the associated ash emissions. In particular, ash emission generated from the fire outbreak is a huge problem during the post-fire cleanup. David has investigated the use of chemical dust suppressants on ash emissions due to Fort McMurray wildfire (paper 401).

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September, 2017

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(MOL) 2016-2017

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Mining Optimization Laboratory (MOL) Researchers / Graduate Students

Following are researchers and students affiliated with Mining Optimization Laboratory in September 2017.

1. **Hooman Askari-Nasab**	Associate Professor - Director of MOL
2. **Yashar Pourrahimian**	Assistant Professor, University of Alberta
3. **Eugene Ben-Awuah**	Assistant Professor, Laurentian University
4. **Kwame Awuah-Offei**	Associate Professor, Missouri S&T

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5. **Mohammad Tabesh**	PhD, Research Associate – 2015/09
6. **Shiv Prakash Upadhyay**	PhD, Research Associate – 2016/09
7. **Saleh Balideh**	PhD, Research Associate – 2016/09
8. **Firouz Khodayari**	PhD Student – 2014/01
9. **Ali Moradi Afrapoli**	PhD Student – 2014/09
10. **Efrain Ugarte-Zarate**	MSc Student (CCG) – 2015/09
11. **Zeinab Basiri**	MSc Student – 2016/09
12. **Vahid Nikbin**	Visiting PhD Student – 2017/07
13. **Farshad Nezhadshahmohammad**	Visiting PhD Student – 2016/09
14. **Navid Seyed Hosseini**	MSc Student – 2015/09
15. **Dylan Caverson**	MEng Student – 2016/01
16. **Ahlam Maremi**	PhD Student – 2015/09
17. **Daniel Ankomah**	PhD Student – 2016/09
18. **Eduardo Cervantes**	MSc Student – 2015/09
19. **Roberto Noriega**	MSc Student – 2017/09
20. **Bright Oppong Afum**	PhD Student – 2017/01
21. **Magreth Dotto**	PhD Student – 2017/09

Linearized Stockpile Modeling for Long-Term Open-Pit Production Planning

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ABSTRACT

Long-term open-pit production planning is a complicated process that includes deciding on the order of extraction of blocks and their destinations in order to satisfy various technical constraints. Moreover, stockpiles can be considered to as buffers of material for future use or sources of high or low-grade ore for controlling blending requirements. In this paper, we present a mathematical formulation that uses aggregated units for making mining, processing and stockpiling decisions while respecting various mining and processing constraints. First, we propose a non-linear model that estimates stockpile grade and controls the head grade of material sent to the processing plants. Next, we use the idea of piecewise linearization to modify the model to be able to solve it with mixed integer linear programming solvers. Afterwards, we show how our model compares against other linear stockpiling models in the literature. Finally, the model is tested on a small dataset to evaluate the performance of the model and show the errors introduced by linearization.

1. Introduction

Open-pit mining is the most common and the oldest method of mining valuable material from the ground. It has attracted many researchers to study various aspects of the operation among which short- to long-term mine planning has been the center of applications of operations research techniques. Various heuristic, meta-heuristic and mathematical programming techniques have been implemented to improve the operation. Long-term plans usually deal with larger units of production and decide on the sequence of extraction of material and their destination. Short-term plans, on the other hand, deal with smaller units and make more detailed decisions. Grade blending and stockpiling is another important aspect present in short- to long-term mine planning. The main two approaches to this is to include the stockpiling decisions while developing a long-term term plan or to develop a long-term plant with no stockpiles and postponing the stockpiling decisions to medium- and short-term plans.

Since Johnson (1969) introduced mathematical programming and in particular linear programming to the mine planning research area many scholars have used the same principles to address the production planning problem in open pit mines. However, no globally recognized solution technique has been obtained yet due to size and complexity of the problem. In addition to the size obstacles, adding stockpiles to the model introduce a non-linear term which make finding the solution even harder. Numerous studies have been published around the long-term open pit

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This paper, in its entirety, is submitted for publication in International Journal of Mining Science and Technology.

production planning problem. Osanloo et al. (Osanloo et al., 2008) and Newman et al. (Newman et al., 2010) provide comprehensive reviews of the literature on this subject to 2010.

Since 2010, Moreno et al. (Moreno et al., 2010) develop a multistep algorithm to solve large-scale LTOPP problems with one capacity constraint. They solve the LP-relaxation of the problem using a critical multiplier procedure and use the results in a TopoSort procedure to obtain good feasible solutions. Bienstock and Zuckerberg (Bienstock and Zuckerberg, 2010) propose a new decomposition based solution method to solve the LP-relaxations of large instances of the LTOPP. They implement and test their algorithm on instances of more than hundred thousand blocks and obtain an LP-relaxation solution in their predefined time threshold. Similarly, Chicoisne et al. (Chicoisne et al., 2012) use decomposition techniques to obtain the LP-relaxation of the LTOPP and use a heuristic technique to find an integer feasible solution to the problem. Cullenbine et al. (Cullenbine et al., 2011) use a sliding time window approach to decompose the LTOPP into smaller problem and solve it. Lambert and Newman (Lambert and Newman, 2014) propose a hybrid solution technique where they obtain an initial feasible solution to the LTOPP and use a modified Lagrangian relaxation to obtain near-optimal solutions. They use two different heuristics for obtaining the initial solution and propose a preprocessing step to set some of the variables to fixed numbers before looking for solutions. Finally, Lamghari et al. (Lamghari et al., 2015) propose a hybrid linear programming and neighborhood search method where they solve an LP for every period using a normalized value for blocks and improve the solution by searching the neighborhood. Using their proposed hybrid method, they report obtaining near-optimal solutions for models with up to 100 thousand blocks in short time periods. However, all these efforts are focused on tackling the size of the problem and not including stockpiles in the planning process.

Bley et al. (2012) model the LTOPP with stockpiling by adding the non-linear constraints and proposing a problem-specific solution method. Moreover, they offer a stronger formulation in which they track the flow of material from aggregates to stockpile and plant. Gholamnejad and Kasmaee (Gholamnejad and Kasmaee, 2012) develop a goal programming model to satisfy the blending requirements of an Iron ore processing plant by blending material from two high grade and low grade stockpiles. Their model provides the optimal reclamation schedule by dividing the stockpiles into blocks and assigning grade values to each block. However, their proposed model does not include decisions on extracting material from the mine and stockpiling and solely focuses on reclamation decisions.

Waqar Ali Asad and Dimitrakopoulos (2012) consider stockpile while determining the cutoff grade in presence of uncertainty. They use the grade-tonnage curves instead of planning units and model the stockpile by using grade ranges and tonnages of material in each range. Ramazan and Dimitrakopoulos (2013) propose a production scheduling model with uncertain supply that includes stockpiling. Their model uses a predetermined constant grade for reclaiming material from the stockpile and allow blocks into the stockpile based on the probability of block grade being within the acceptable range for the stockpile. However, the authors do not compare the actual grade of material in the stockpile to the predefined grade.

Smith and Wicks (2014) propose an MIP for medium-term production planning with stockpiling in a copper mine. The authors divide ore into different categories based on low and high grade and recovery of the main two elements and define a stockpile for rehandling low-grade ore when needed. However, they avoid nonlinearity by not keeping track of elements grades going to and reclaimed from the stockpile. Mousavi et al. (2016) also consider stockpiling with a predetermined grade and use a non-exact approach deal with the problem. They compare their results against solutions obtained via exact method and show how close to the optimum solution their solutions are. However, they do not study the errors caused by assuming a fixed reclamation grade for the stockpile and their largest case-study has 2,500 blocks which is a relatively small number.

Kumar and Chatterjee (2017) propose and apply a mathematical formulation for production scheduling with stockpiling in a coal mine. Their formulation follows the same approach and assumes a fixed predetermined reclamation grade for the stockpile and show that the observed element head grades are within the required boundaries. Finally, Moreno et al. (2017) classify the production scheduling and stockpiling models in the literature and propose a new modeling approach. Moreover, they provide extensive computational results for the models they studied and developed. We will discuss their proposed model in the next chapter in more details.

In this paper, we present a mixed integer linear programming model for long-term multi-destination open-pit production planning problem that uses two sets of aggregated units for making mining and processing decisions and incorporates the blending constraints and stockpiling. The model is a continuation of our work on long-term open-pit production planning started by aggregating blocks into larger mining-cuts in (2011), formulating an MILP for optimizing the production schedule in (2014) and adding stockpiles to the formulation in (2015).

2. Mathematical Formulations

As mentioned earlier, various LTOPP mathematical models have been proposed in the literature. In this paper, we tried to model stockpiling while avoiding the non-linear constraints by benefiting from the piecewise linearization technique. In order to model the stockpile element grade we introduce multiple stockpiles with different acceptable grades to be able to assign fixed reclamation grades to each stockpile. These input grade ranges, as well as reclamation grades, are determined based on histograms of grades to be representative of data prior to solving the model. Moreover, we decrease the problem size by using two different sets of aggregates to make mining and processing decisions: bench-phases (intersections of benches and pushbacks) are used to make mining scheduling decisions and mining-cuts are used to make destination decisions. The mining cuts are generated through a clustering algorithm that not only accounts for the similarities but also respects the size and shape constraints. The clustering algorithm mentioned is a variation of hierarchical agglomerative clustering and is thoroughly explained in (2013). We use the clustering algorithm to create processing units within the boundaries of bench-phases. Therefore, the bench-phases are divided into smaller units with similar rock-type and grade which are the basis for making processing and stockpiling decisions. The mathematical formulation and notations are an improved and tailored versions of the model presented in (2015).

- 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

$y_m^t \in [0,1]$	Continous decision variable representing the portion of bench-phase m extracted in period t
$x_{p,c}^t \in [0,1]$	Continous 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	Continous decision variable representing the tonnage reclaimed from the stockpile and sent to processing plant c in period t
$G^{t,e}$	Continous decision variable representing the reclamation grade of element e in period t

2.1. Non-linear Model

We first present the original LTOPP with stockpiling mathematical model with non-linear stockpile grade calculation. The model is a multi-destination LTOPP which uses two different sets of units for making mining and processing decisions. Two sets of variables are defined for bench-phases: $y_m^t \in [0,1]$ is the portion of bench-phase extracted in each period and $b_m^t \in \{0,1\}$ is the binary variable to control the precedence. Since the number of bench-phases is less than number of blocks and clusters, controlling the precedence with bench-phases results in less binary variables and less resource consumption for solving the model. Moreover, using bench-phases as mining units is the common practice in the mining industry. However, making material destination decisions requires more accurate units with distinction between ore and waste. This is achieved by dividing every bench-phase into smaller units using the clustering algorithm.

- Objective Function

$$\max \sum_{t=1}^{T}\left(\sum_{p=1}^{P}\sum_{c=1}^{C}(r_{p,c}^t \times o_p \times x_{p,c}^t) - \sum_{m=1}^{M}(c_m^t \times (o_m + w_m) \times y_m^t) + \sum_{e=1}^{E}\sum_{c=1}^{C}\left(f_c^t \times G^{t,e} \times r_c^{t,e}\right)\right) \tag{1}$$

- Constraints

$$\underline{MC}^t \le \sum_{m=1}^{M}\left((o_m + w_m)\times y_m^t\right) \le \overline{MC}^t \qquad \forall t \in \{1,...,T\} \tag{2}$$

$$\sum_{p \in U^m}\sum_{d=1}^{D}\left(o_p \times x_{p,d}^t\right) \le (o_m + w_m)\times y_m^t \qquad \forall t \in \{1,...,T\}, \forall m \in \{1,...,M\} \tag{3}$$

$$\underline{PC}_c^t \le \sum_{p=1}^{P}\left(o_p \times x_{p,c}^t\right) + f_c^t \le \overline{PC}_c^t \qquad \forall t \in \{1,...,T\}, \forall c \in \{1,...,C\} \tag{4}$$

$$\underline{G}_c^{t,e} \le \frac{\sum_{p=1}^{P}\left(o_p \times g_p^e \times x_{p,c}^t\right) + f_c^t \times G^{t,e}}{\sum_{p=1}^{P}\left(o_p \times x_{p,c}^t\right) + f_c^t} \le \overline{G}_c^{t,e} \qquad \forall t \in \{1,...,T\}, \forall c \in \{1,...,C\}, \forall e \in \{1,...,E\} \tag{5}$$

$$G^{t,e} = \frac{\sum_{p=1}^{P}\left(o_p \times g_p^e \times x_{p,c'}^t\right) - \sum_{t'=1}^{t-1}\sum_{c=1}^{C} f_c^{t'} \times G^{t',e}}{\sum_{p=1}^{P}\left(o_p \times x_{p,c'}^t\right) + \sum_{t'=1}^{t-1}\sum_{c=1}^{C} f_c^{t'}} \qquad \forall t \in \{1,...,T\}, \forall e \in \{1,...,E\} \tag{6}$$

$$\sum_{t'=1}^{t}\sum_{c=1}^{C} f_c^{t'} \le \sum_{t'=1}^{t-1}\sum_{p=1}^{P}\left(o_p \times x_{p,c'}^{t'}\right) \qquad \forall t \in \{2,...,T\} \tag{7}$$

$$\sum_{t=1}^{T} y_m^t = 1 \qquad \forall m \in \{1,...,M\} \qquad (8)$$

$$\sum_{i=1}^{t} y_m^i \le b_m^t \qquad \forall m \in \{1,...,M\}, \forall t \in \{1,...,T\} \qquad (9)$$

$$s_m \times b_m^t \le \sum_{i \in S^m} \sum_{j=1}^{t} y_i^j \qquad \forall m \in \{1,...,M\}, \forall t \in \{1,...,T\} \qquad (10)$$

$$b_m^t \le b_m^{t+1} \qquad \forall m \in \{1,...,M\}, \forall t \in \{1,...,T-1\} \qquad (11)$$

The objective function (equation (1)) is summation of discounted revenue made from sending material to the processing plants directly from the mine and reclaiming from the stockpile minus the total cost of mining material from the ground. Equations (2) and (4) are responsible for controlling the minimum and maximum extraction and processing capacity in each period. Equation (3) controls the relation between the tonnage mined from each bench-phase and the tonnage processed from the clusters within that bench-phase. Note that the difference between the tonnage extracted and the tonnage processed is the waste extracted and sent to the waste dump. However, if we have a waste dump with an extra haulage cost the dump can be defined as a destination with negative revenue. Equation (5) controls the average head grade of material sent to processing plants in each period by averaging the grade of material sent directly from the mine with the average grade of material reclaimed from the stockpile. However, to avoid non-linearity the equations are rearranged before putting into matrix format. Equation (8) ensures that all the material within the ultimate pit is extracted during mine life, and Equations (9) to (11) are the precedence control constraints with the binary variables.

The stockpile is added as a destination with the index of c' to control the tonnage and grades of material sent to the stockpile using the same constraints as for the processing plants. $G^{t,e}$ is the reclamation grade of element e in period t and is calculated using equation (6). Note that the objective function and equation (6) are non-linear equations. Equation (7) ensures that the summation of tonnages reclaimed from stockpile from the first period to the current period does not exceed the summation of tonnages sent to the stockpile by the current period. The constraint is defined using the cumulative sent and reclaimed tonnages to avoid introducing extra variables for keeping track of the stockpile inventory.

2.2. Linearized Model

In order to have a linear LTOPP model with stockpiling, we assume that there are multiple stockpiles with tight ranges for the acceptable element grades. Therefore, we can assign an average reclamation grade and the corresponding reclamation revenue to each stockpile. The more stockpiles defined the smaller error is introduced into the model. However, more stockpiles sacrifices the complete blending assumption present in most stockpiling scenarios. Therefore, making reasonable assumptions regarding the number of stockpiles to define and the acceptable element grade ranges is crucial to obtaining reasonable results.

In order to create the linear LTOPP model with stockpiling we define S stockpiles and add S destinations for materials to the list of processing plants. $G_s^{e,t}$ is the predetermined average reclamation grade of element e from stockpile s in period t, and $r_{s,c}^t$ is the unit discounted revenue of reclaiming material from stockpile s with the average grade and processing them in plant c in period t minus the processing and rehandling costs. $\underline{G}_d^{e,t}$ and $\overline{G}_d^{e,t}$ are the lower and upper bounds on the acceptable average element grade e for stockpile destination $d = C + s$.

$f_{s,c}^{t} \geq 0$ is the set of variables representing the tonnage of material reclaimed from stockpile s in period t and sent to processing destination c. Now we can rewrite the model by replacing the objective function with equation (12) and equations (4) to (7) with equations (13) to (16) respectively. Moreover, we add a constraint on the element content of the material sent to stockpile and the element content of material reclaimed from the stockpile while avoiding non-linear grade control. Equation (17) ensures that reclaiming from the stockpile is stopped if the predetermined average grade is significantly higher than the actual grade of material sent to the stockpile. For example, if 100 tonnes of ore with average element grade of 5% is sent to the stockpile and the reclamation grade is assumed to be 10%, the model will limit the reclamation to 50 tonnes.

$$\max \sum_{t=1}^{T}\left(\sum_{p=1}^{P}\sum_{c=1}^{C}(r_{p,c}^{t} \times o_p \times x_{p,c}^{t}) - \sum_{m=1}^{M}(c_m^t \times (o_m + w_m) \times y_m^t) + \sum_{s=1}^{S}\sum_{c=1}^{C}\left(f_{s,c}^{t} \times r_{s,c}^{t}\right)\right) \tag{12}$$

$$\underline{PC}_c^t \leq \sum_{p=1}^{P}\left(o_p \times x_{p,c}^t\right) + \sum_{s=1}^{S} f_{s,c}^t \leq \overline{PC}_c^t \qquad \forall t \in \{1,...,T\}, \forall c \in \{1,...,C\} \tag{13}$$

$$\underline{G}_c^{t,e} \leq \frac{\sum_{p=1}^{P}\left(o_p \times g_p^e \times x_{p,c}^t\right) + \sum_{s=1}^{S}\left(f_{s,c}^t \times G_s^{t,e}\right)}{\sum_{p=1}^{P}\left(o_p \times x_{p,c}^t\right) + \sum_{s=1}^{S} f_{s,c}^t} \leq \overline{G}_c^{t,e} \qquad \forall t \in \{1,...,T\}, \forall c \in \{1,...,C\}, \forall e \in \{1,...,E\} \tag{14}$$

$$\underline{G}_d^{t,e} \leq \frac{\sum_{p=1}^{P}\left(o_p \times g_p^e \times x_{p,d}^t\right)}{\sum_{p=1}^{P}\left(o_p \times x_{p,d}^t\right)} \leq \overline{G}_d^{t,e} \qquad \forall t \in \{1,...,T\}, \forall e \in \{1,...,E\}, \forall d \in SC \,\middle|\, d = C + s \tag{15}$$

$$\sum_{i=1}^{t}\sum_{c=1}^{C} f_{s,c}^i \leq \sum_{i=1}^{t-1}\sum_{p=1}^{P}\left(o_p \times x_{p,d}^i\right) \qquad \forall s \in \{1,...,S\}, \forall t \in \{2,...,T\}, \forall d \in SC \,|\, d = C + s \tag{16}$$

$$\sum_{i=1}^{t}\sum_{c=1}^{C} G_s^{t,e} \times f_{s,c}^i \leq \sum_{i=1}^{t-1}\sum_{p=1}^{P}\left(o_p \times g_p^e \times x_{p,d}^i\right) \qquad \forall s \in \{1,...,S\}, \forall t \in \{2,...,T\}, \forall e \in \{1,...,E\}, \forall d \in SC \,|\, d = C + s \tag{17}$$

2.3. Comparison with other models

As mentioned earlier, we have developed a mathematical model to simultaneously make decisions on the extraction of material from the mine, destination of material extracted and the stockpiling scenarios in long-term horizon. The LTOPP has been widely studied and modeled using various approaches, however, the LTOPP with stockpiling option has not been as widely studied. Moreno et al. (2017) present and compare the most common modeling approaches and propose a new model for linear modeling of stockpile. In this section, we show how our proposed model compares against some of the studied approaches taken towards modeling the stockpiles.

In order to compare the models, we need to modify and simplify our model depending on the model we are comparing against. First simplification is that we only need one processing destination and one element of interest. Thus, we remove indices $e \in \{1,...,E\}$, assuming that $E = 1$, from all variables and parameters. It is an important change especially for processing operations that are sensitive to the grade of deleterious elements in the ore. Next, we need to use blocks for making mining and processing decisions. Therefore, both variables $x_{p,c}^t \in [0,1]$ and

$y_m^t \in [0,1]$ should be defined for blocks as $x_{b,c}^t \in [0,1]$ and $y_b^t \in [0,1]$. Furthermore, in all cases the blocks are assumed to be completely ore or waste. Therefore, we will replace o_b and $o_b + w_b$ with W_b as used in (2017). Another modification required is to replace grade of blocks with metal contents. It is an easy modification since the grade is a known parameter and we can always multiply the tonnage of a block by the grade to obtain the metal content $M_b = W_b \times g_b$. Now, we will compare our model against the linear L-bound, K-bucket and L-Average models in (2017). The L-bound and L-Average models use only one stockpile, and therefore, we will set $S = 1$ in our model to limit our model to one stockpile. Moreover, since there is only one processing plant and one stockpile we limit $c \in \{1,...,C\}$ to $c \in \{1,2\}$ where destination 1 is the processing plant and destination 2 is the stockpile. The L-bound model uses a lower bound for the grade of blocks sent to the stockpile and assumes a fixed reclamation grade for the stockpile. As pointed out by (2017), this model is too conservative and can be improved by controlling the average grade of material sent to the stockpile instead of individual block grades. However, in order to obtain the same result with our model we need to replace equation (15) with equation (18) and use a large upper bound on the average input grade for the stockpile.

$$x_{b,2}^t = 0 \qquad \begin{array}{l} \forall t \in \{2,...,T\}, \\ \forall b \in \{1,...,B\} \big| g_b < \underline{G}_2^t \end{array} \tag{18}$$

Following the same approach as for the L-bound model we can obtain the K-bucket model by defining $S = K$ stockpiles and replacing equation (15) with equation (19). However, in order to obtain the L-Average model we do not need to add or modify any constraints. We can obtain the L-Average model by limiting our model to one processing destination and one stockpile and changing to notations.

$$x_{b,1+s}^t = 0 \qquad \begin{array}{l} \forall t \in \{2,...,T\}, \forall s \in \{1,...,S\}, \\ \forall b \in \{1,...,B\} \big| g_b < \underline{G}_{1+s}^t \end{array} \tag{19}$$

3. Case Study

In order to evaluate the proposed model and quantify the error introduced by linearizing the stockpile grade calculation we implemented the model on an iron-ore block model. The dataset contains 430 million tonnes of material in the final pit discretized into 19,561 blocks. The goal is to obtain a long-term plan over 20 years of production with three years of pre-stripping. The dataset is divided into four pushbacks using the parameterization approach which results in 40 bench-phases. Afterwards, the hierarchical clustering with shape control technique from Tabesh and Askari-Nasab (2013) is implemented on the dataset resulting in 1870 mining-cuts.

The processing plant capacity is seven million tonnes per year starting from year four of the operation. The mining capacity is 32 million tonnes at the beginning of the operation and is gradually decreased to eight million tonnes towards the end of the mine life. The block model contains seven different rock types (three ore and four waste) and tracks three different elements. Iron content is tracked via mass percent of magnetic weight (MWT) and deleterious elements Sulfur (S) and Phosphor (P) are tracked in mass percent units. The processing plant specifications require ore with a minimum MWT of 78% and maximum P and S content of 0.14% and 1.7% respectively.

We formulated the models in Matlab and solved them to optimality using Gurobi (2017) optimization engine. The clustering algorithm takes 5 seconds to group blocks into clusters and all the models are solved to optimality in less than 15 seconds.

3.1. Original Schedule

We first run the MILP without any constraints of the head grade to adjust the mining capacity for an acceptable schedule. We will use the same settings for the next scenarios to show how the stockpile can help the mine planner and we will also show the errors introduced by using a linear stockpile model. The original schedule with no head grade constraint is presented in Figure 1. The head grade for P and MWT is presented in Figure 2. The plant Sulfur head grade constraint is not binding for any of the scenarios and is omitted from graphs to make them easier to read. It can be seen that MWT and P requirements are not met specially in the earlier periods where access to high quality ore is limited. The generated schedule results in NPV of 2,615 million dollars.

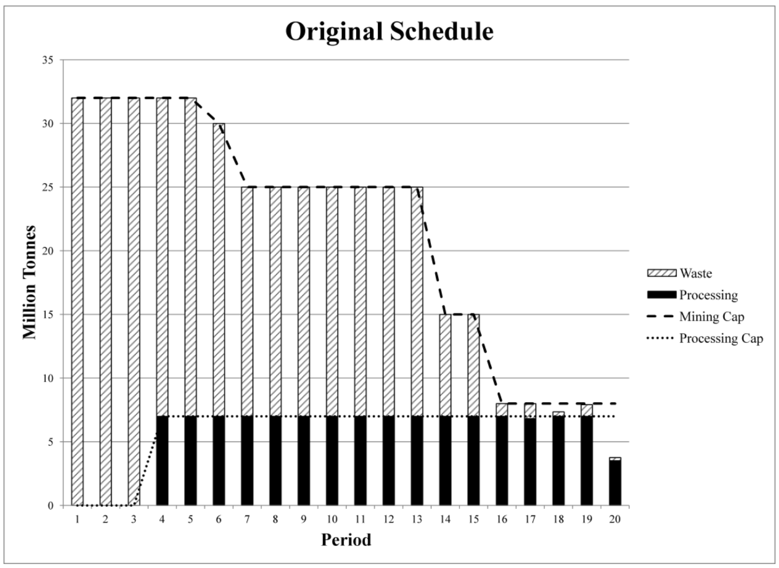

Figure 1.Original Schedule

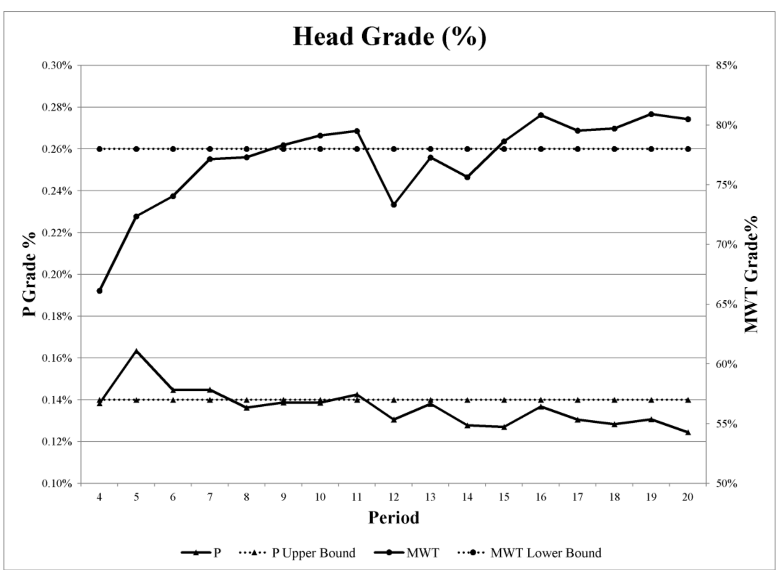

Figure 2.Head Grade in Original Schedule

3.2. Head Grade Constraints

Now we will add the head grade constraints for the three elements and run the MILP again. The schedule presented in Figure 3 shows that plant is not fully utilized in most years. Moreover, since there is no ore extracted in period four since the grade of ore is not acceptable for the plant. The generated NPV is also dropped to 2,109 million dollars which is a 23% decrease.

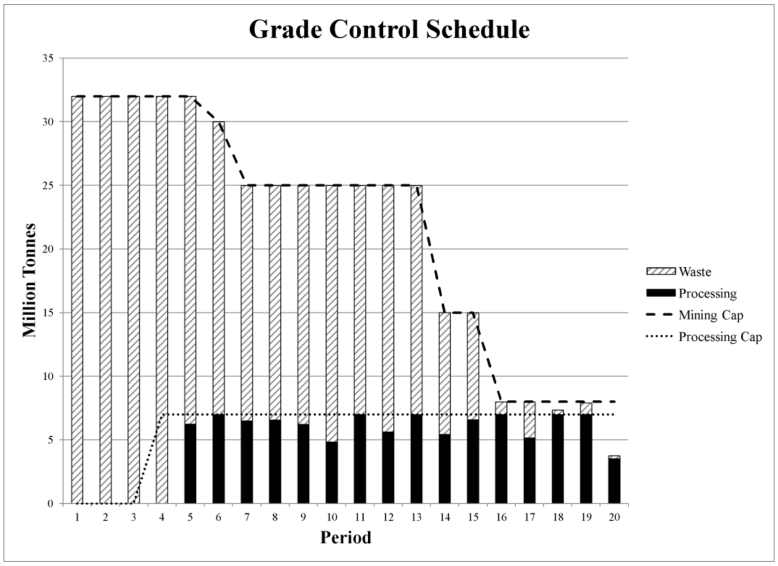

Figure 3.Grade Control Schedule

3.3. Single Stockpile

Now we will add a stockpile to help the operation balance the head grade. The stockpile is defined with average input grade ranges and reclamation grades presented in Table 1. Since the relationship between the elements of interest is not linear the tonnage of material within the ranges varies by changing the stockpile ranges. Figure 4 shows the range of mining-cut grades allowed to the stockpile. The reclamation grade is calculated based on the average grade of ore within the acceptable stockpile input grade. The revenue of reclaiming material from the stockpile and sending to plant is calculated based on the MWT reclamation grade and a rehandling cost of \$0.5/tonne. It is worth noting that the mining fleet require for reclamation is assumed to be independent of the mining fleet. As can be seen in Figure 5 the plant is fully utilized in all years except than year four where there is not enough high quality ore to feed the plant. However, the ore is stored in stockpile and reclaimed in later years while being mixed with higher quality ore and fed to the plant. The resulted NPV is 2,291 million dollars which is 9% higher than the no stockpile scenario. Figure 6 shows the difference between the actual grade of material in stockpile and the predetermined reclamation grade. It is obvious that the optimizer tried to send material with lower MWT and higher P grade to the stockpile and take advantage of the better reclamation grade to increase the NPV while respecting the head grade constraint. The average absolute error in grade is 11.6% and the total material reclaimed from the stockpile over the mine life is 12 million tonnes.

Table 1.Single Stockpile Parameters

Stockpile	Element	$\underline{G}_d^{t,e}$ (%)	$\overline{G}_d^{t,e}$ (%)	$G_s^{t,e}$ (%)
1	P	0.10	0.15	0.13
	S	1.00	2.00	1.59
	MWT	70.00	80.00	76.55

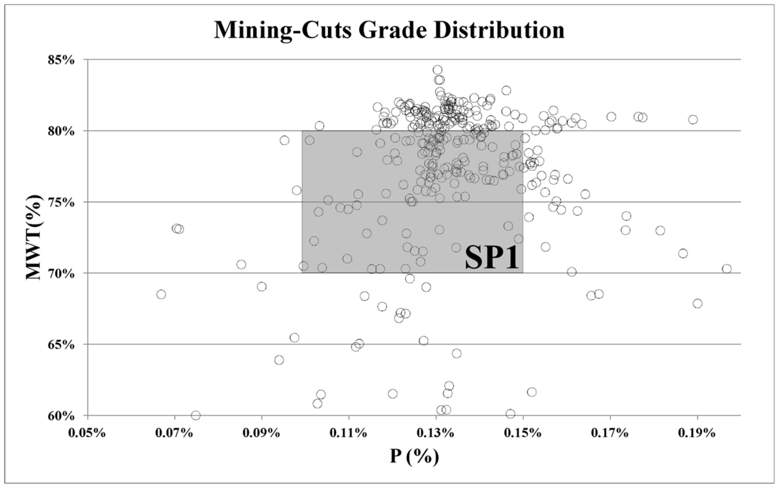

Figure 4.Single Stockpile Range

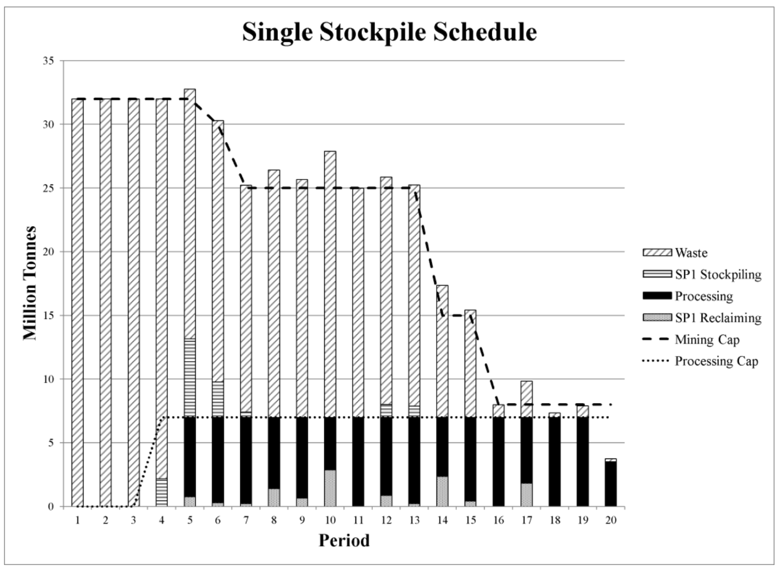

Figure 5.Single Stockpile Schedule

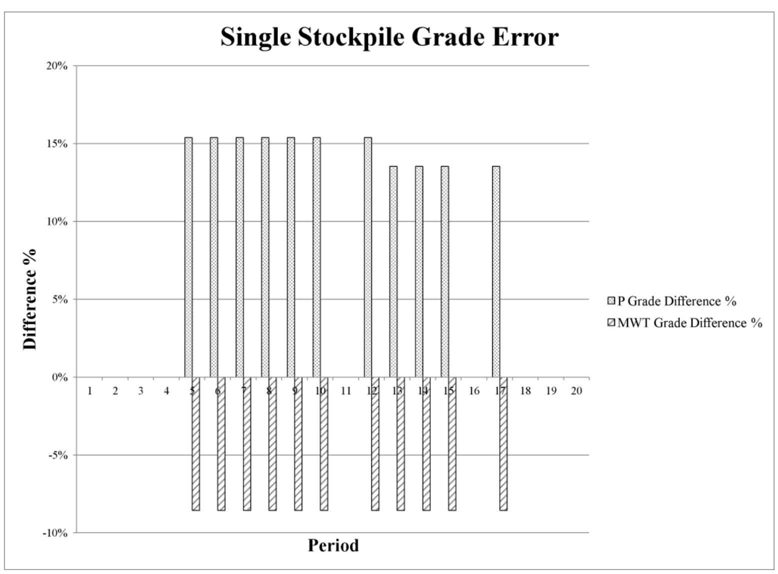

Figure 6.Single Stockpile Grade Error

3.4. Double Stockpile

Now we will add another stockpile to tighten the ranges of the acceptable grades and decrease the errors with the parameters provided in Table 2. The range of mining-cuts that are within the acceptable ranges for the stockpiles in shown in Figure 7. You can see how the difference between grade ranges affects the mining-cut ranges in Figure 4 and Figure 7.

Table 2.Double Stockpile Parameters

Stockpile	Element	$\underline{G}_d^{t,e}$ (%)	$\overline{G}_d^{t,e}$ (%)	$G_s^{t,e}$ (%)
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

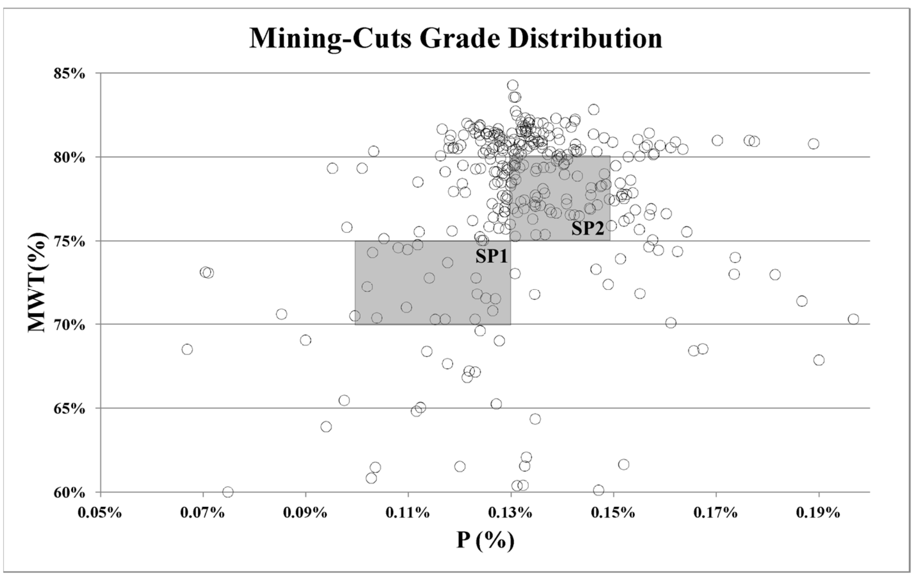

Figure 7.Double Stockpile Range

Figure 8 shows the production schedule with two stockpiles that results in an NPV of 2,234 million dollars. This is 5.5% higher than the no stockpile scenario and 2.6% lower than the single stockpile scenario. Note that no extra cost has been considered for building and maintaining the stockpiles and the 2.6% difference is due to decreasing the error introduced by predetermined stockpile grade assumption.

Figure 9 shows the difference between the actual grade of material in stockpile and the predetermined reclamation grade. The average absolute error in grade is 6.5% and the total material reclaimed from the stockpiles over the mine life is 8 million tonnes.

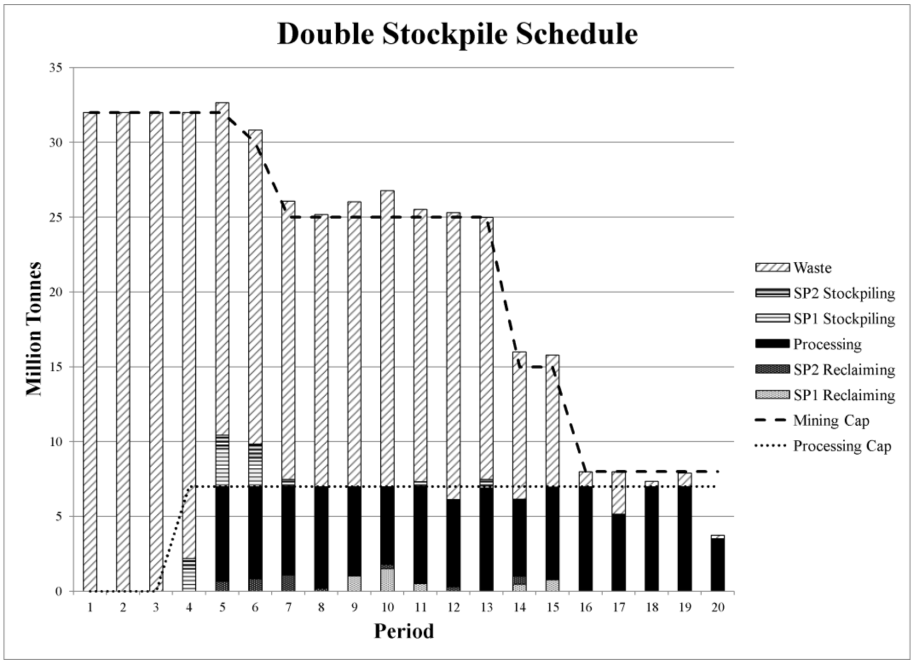

Figure 8.Double Stockpile Schedule

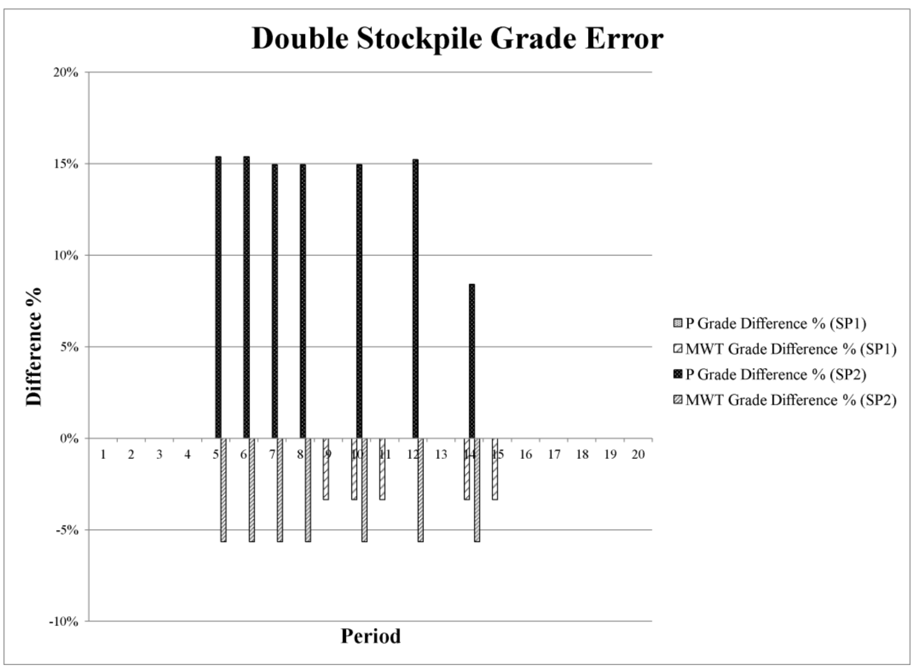

Figure 9.Double Stockpile Grade Error

3.5. Triple Stockpile

We further increase the number of stockpiles to three to study the effects of tightening the grade range for input to stockpiles. The three stockpile parameters are provided in Table 3. The area covered by stockpile input ranges shrinks compared to less number of stockpiles as shown in Figure 10. Using three stockpiles results in an NPV of 2,155 million dollar which is 3.4% less than the double stockpile scenario and 2.3% higher than no stockpile scenario. The average absolute error in grade is 3% and the total material reclaimed from the stockpiles over the mine life is 6 million tonnes.

Table 3.Triple Stockpile Parameters

Stockpile	Element	$\underline{G}_d^{t,e}$ (%)	$\overline{G}_d^{t,e}$ (%)	$G_s^{t,e}$ (%)
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

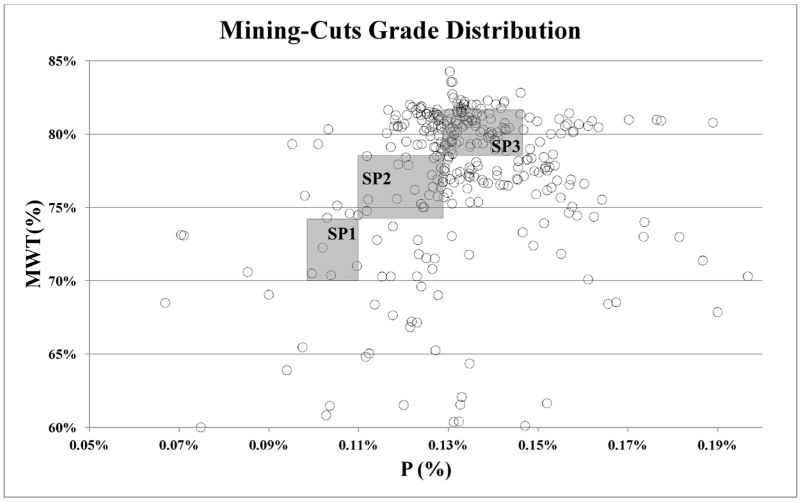

Figure 10.Triple Stockpile Range

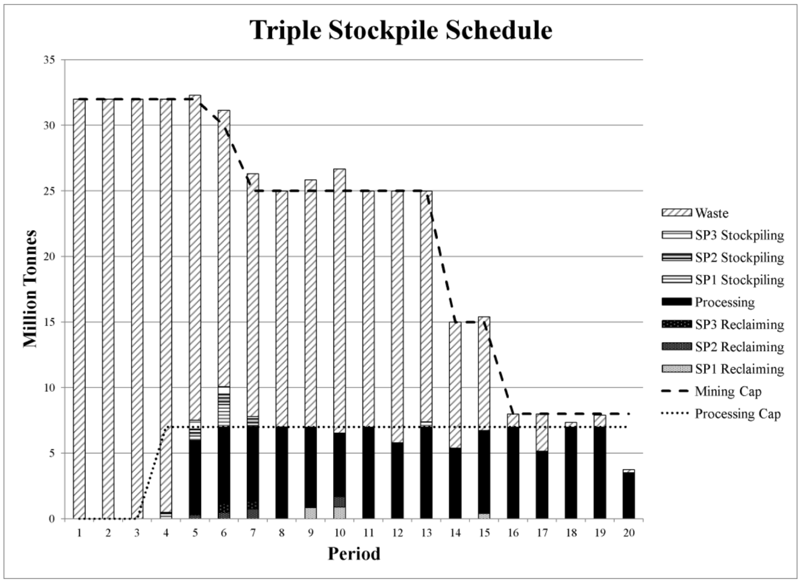

Figure 11.Triple Stockpile Schedule

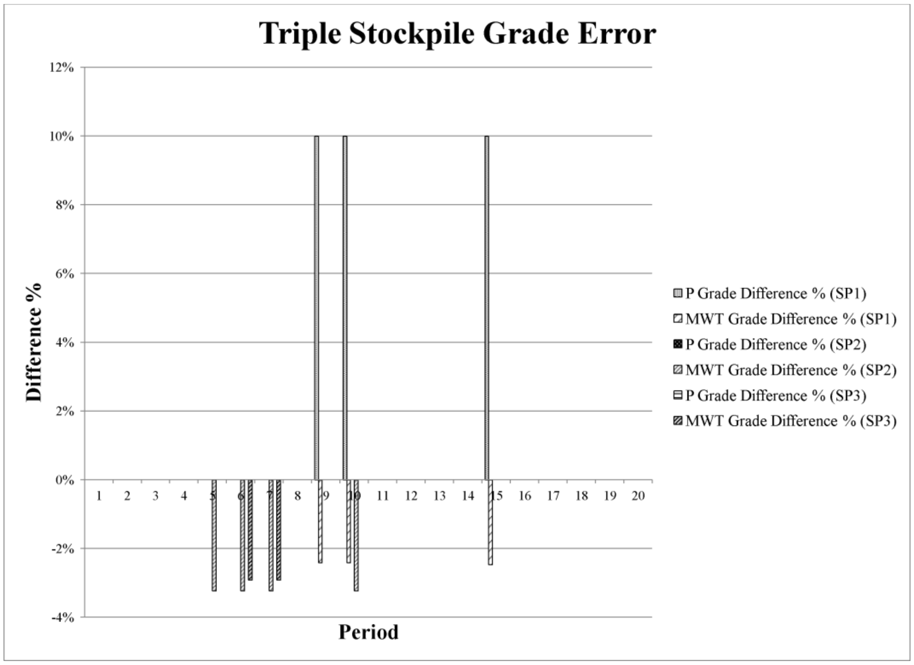

Figure 12.Triple Stockpile Grade Error

3.6. Quadruple Stockpile

In order to avoid changing the number of mining-cuts that are allowed to be sent to the stockpiles and obtain a solution comparable to single stockpile scenario, we created a scenario with four stockpiles in which the defined ranges cover the same area, as can be seen by comparing Figure 13 against Figure 4. Since we are controlling two elements at the time, we need four stockpiles to cover the same range. The four stockpile parameters are provided in Table 3. Using four stockpiles results in an NPV of 2,331 million dollar which is 1.7% higher than the single stockpile scenario and 10.5% higher than no stockpile scenario. The average absolute error in grade is 5.1% and the total material reclaimed from the stockpiles over the mine life is 12.1 million tonnes.

Table 4.Quadruple Stockpile Parameters

Stockpile	Element	$\underline{G}_d^{t,e}$ (%)	$\overline{G}_d^{t,e}$ (%)	$G_s^{t,e}$ (%)
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

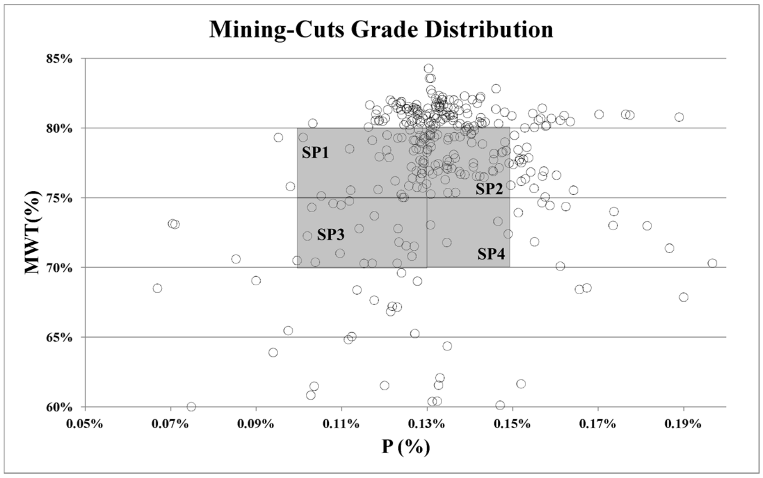

Figure 13. Quadruple Stockpile Range

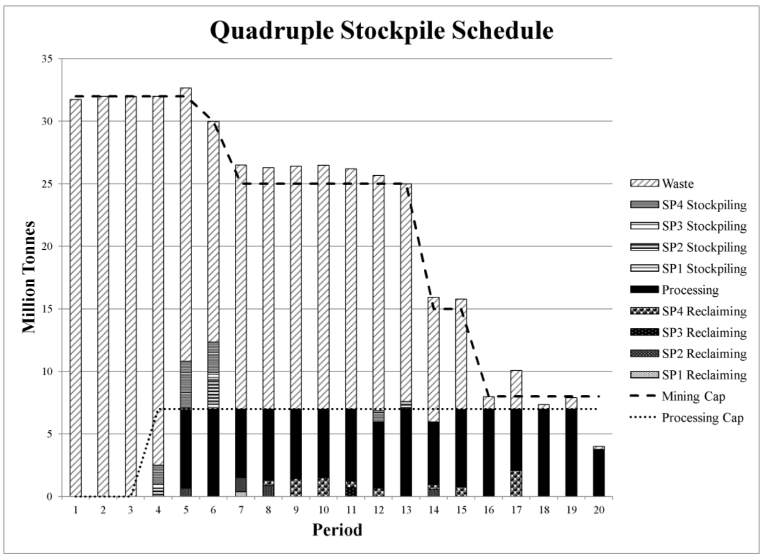

Figure 14. Quadruple Stockpile Schedule

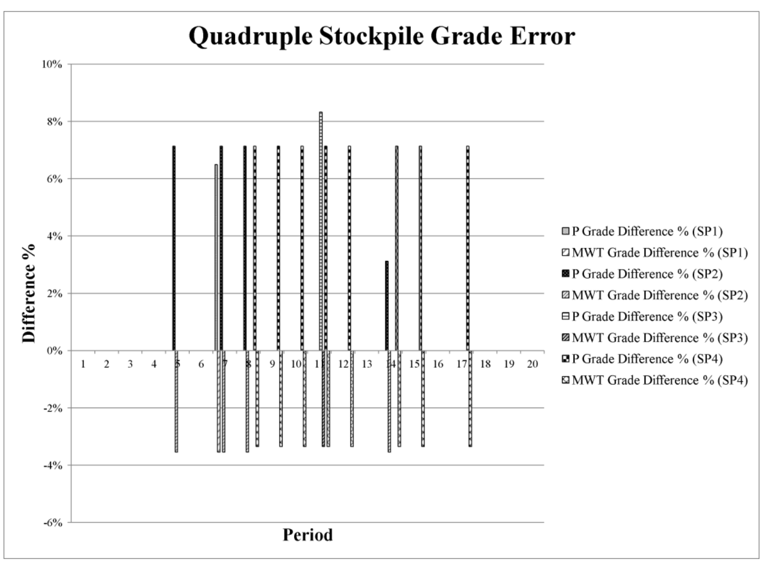

Figure 15. Quadruple Stockpile Grade Error

3.7. Summary of the results

We tested our proposed model on multiple scenarios in an Iron ore mine. We started by obtaining an acceptable schedule for the operation without restricting the grade of material sent to the processing plant. As expected, this scenario resulted in the highest NPV and we use this as the benchmark for calculating difference percentages for other scenarios.

As can be seen in Table 5, the no stockpile scenario results in the lowest NPV and even fails to feed the plant properly (Figure 3). Therefore, we added stockpiles to feed the plant and increase the NPV. However, there is a linearization error associated with each stockpile which we are trying to quantity. Thus, we devised four different stockpiling scenarios. Scenarios with one, two and three stockpiles follow the same trend where tightening the ranges of stockpile inputs and increasing the number of stockpiles decreases the resulted NPV, the total tonnage of material reclaimed from the stockpiles and the average grade estimation error. As shown in the previous sections, controlling multiple element grades for the stockpiles input plays a significant role in the way we define our stockpiles and estimate the reclamation error. Finally, we tested a scenario where four stockpiles covered the same grade range as the single stockpile and showed that the average grade estimation error can be decrease without decreasing the usability of the stockpiles.

Table 5.Summary of the results

Scenario	NPV ($M)	Diff (%)	CPU Time (s)	Reclaimed Tonnage (MT)	Average Grade Error (%)
No limit	2615	0	0.99	-	-
Grade Control	2108	-19%	2.17	-	-
Single SP	2291	-12%	4.17	12.0	11.6
Double SP	2234	-14%	8.43	8.2	6.5
Triple SP	2155	-18%	8.82	5.7	3.0
Quadruple SP	2231	-15%	15.86	12.0	5.1

4. Conclusion and future work

In this paper, we presented continuation of our work on LTOPP by including stockpiling in the long-term plan formulation. We presented the original non-linear model and showed how we can benefit from piecewise linearization and develop a linear model. We compared our linear model against variety of models proposed in the literature and showed the differences and similarities. In the third section, we presented a case study to show the effects of adding stockpiles to long-term production plans and the effects of defining stockpile grade ranges when dealing with linearized grade estimations in the MILP. We started by showing how having constraints on the input grade of material into the processing plant affects the production schedule and how adding stockpiles can help to overcome the shortcomings. Afterwards, we presented multiple stockpiling scenarios to study the errors introduced by linearly estimation of stockpile output grades.

We first defined one stockpile with control over the average grade of material sent to the stockpile. We showed that having one stockpile in place can prevent shortfalls in plant feed. However, the linear estimation of output grade incurred an 11.5% error. We then increased the number of stockpiles by tightening the ranges of acceptable materials for each stockpile and showed how it can decrease the error. Moreover, we illustrated how controlling multiple element grades increases the complexity of stockpile estimations and limits the tonnages of material that can go into the stockpiles. Finally, we presented a case where four stockpiles cover the same grade range as the single stockpile and showed that it is possible to decrease the estimation error and allow the same tonnage of material into the stockpile. However, deciding on the number of stockpile and their grade ranges will heavily depends on the characteristics of deposit and operation due to homogenous reclamation and other important stockpiling assumptions. Moreover, our work highlighted an important shortcoming in the studies of stockpiling in open-pit mines where most approaches assume a single element of interest and ignore the errors and effects of other elements.

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A Multi Objective Multi Stage Mining Fleet Management System Linking Dynamic Operation to Short-Term Plan

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ABSTRACT

Fluctuation in market price of mineral products has enforced mining companies to cut down their operating costs. One useful way of reducing operating costs in mining operations is to make optimal operational decisions, incorporating efficient mining fleet management systems (FMS). Since 50 years ago several types of FMS have been developed and introduced in the mining systems around the world. However, there are two major shortcomings in existing systems. Firstly, none of the existing systems consider effects of the short-term plan on dynamic truck assignment. Secondly, most of the existing FMS make decisions in a way that optimize a specific objective while ignoring others. Herein, we propose a multi stage and multi objective FMS that deals with aforementioned shortcomings of the currently available systems. The developed FMS, in its upper stage, links semi-dynamic operational decision making process to the short-term production plan by simultaneously assigning shovels to mining faces and allocating trucks to the shovels by implementing its first multi objective decision making model. Then in its second stage, in a real time dynamic decision making process, it assigns trucks to shovels and corresponding destinations by optimizing its second multi objective decision making model. The developed fleet management system has been verified using an Iron ore case study and the results are presented in this paper.

1. Introduction

Open pit mining method is the most common method to mine mineral from the earth. Based on (Wetherelt and van der Wielen, 2011) there exist 2500 open pit metal mines that are categorized as industrial scale mines. Several methods of material handling are used in to mine these open pit mines including dragline systems, bucket-wheel excavator systems, truck and shovel material handling systems, and etc. However, the amount of material handled using truck and shovel material handling system is more than the amount handled by all other systems together (Humphrey and Wagner, 2011). Because of that, studying truck and shovel mining operation is a matter of interest among the researchers working in the area of open pit mining. Fig. 1 shows a general scheme of an open pit mining operation with N digging points and M material dumping point connected to each other. It has been proven by several studies that more than 50 percent of operating cost in a truck and shovel based open pit mining operation is accounted for material handling (Alarie and Gamache, 2002; Ahangaran et al., 2012; Moradi Afrapoli and Askari-Nasab, 2017). Thus, introducing even 1 to 2 percent cut in its material handling cost saves huge amount of money for the stakeholders. To introduce that cut, two main ways have been used over the last 50 years. On one hand mining industries have been implementing equipment with higher production capacities, and on the other hand, researchers have been developing operation research techniques to make required decisions as close to optimal as possible to deduct operational costs in truck and shovel based mining operations.

Many decisions need to be make optimally in any open pit mine. These are included but not limited to Long-/Medium-/Short-term production planning (Bley et al., 2010; Shishvan and Sattarvand, 2015; Jélvez et al., 2016), ultimate pit determination (Rodovalho et al., 2016), fleet selection and size determination (Beaulieu and Gamache, 2006), finding the shortest paths (Ferone et al., 2016; Breugem et al., 2017), production optimization (White and Olson, 1986; Temeng et al., 1998; Ta et al., 2005; Gu et al., 2010; Topal and Ramazan, 2010; Upadhyay and Askari-Nasab, 2016; Chaowasakoo et al., 2017; Patterson et al., 2017), equipment maintenance and repair (Topal and Ramazan, 2012), fuel consumption (Soofastaei et al., 2016), and truck dispatching (White and Olson, 1986; Soumis et al., 1989; Temeng et al., 1997). Over the last decades several studies have been conducted in each of the above mentioned parts of decision making procedure in open pit mining operation optimization. However, one of the most important decision making tool in any open pit mining operation is fleet management system. After finding shortest paths, a fleet management system, as is presented in Fig. 2, makes required semi-dynamic and dynamic decisions in two steps. In the first step of its decision making procedure, it decides on optimum amount of material to be transported from a specific loading zone to a dumping location based on the objective function and the constraints defined for the model (Fig. 1). Then, each and every time a truck requires an assignment, the lower stage of the fleet management system finds a destination for the truck based on predetermined criteria.

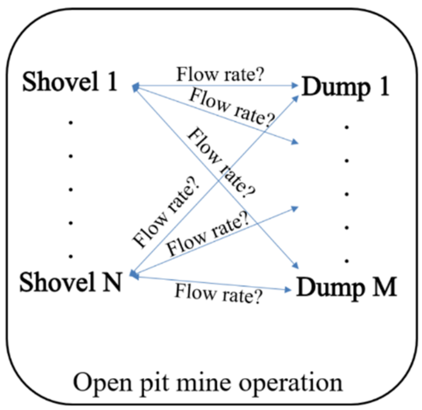

Fig. 1: Schematic of an open pit mining operation

Since late 1960s number of research have been done in both industries and academies to enhance productivity and reduce cost of mining operation by developing flexible allocation models and algorithms based on different strategies.

First, Bogert (1964) suggested the use of radio communication between equipment operators and the mine control centre. Then in the next decade, one of the first algorithms introduced to solve truck allocation and dispatching problem in open pit mines is a single stage algorithm presented by Hauck (1973). The main feature of presented algorithm is combination of operation plan and real-time scheduling in a single model. The model is based on solving a sequence of assignment problem by using of Dynamic Programming (DP). The model considers stripping ratio, blending objectives, capacity of the plant and stockpile. In the late 1970s, Mueller (1977) introduced implementation of the dispatching boards installed in the control centre using a simplified dispatching technique to manage the operation.

Although some research had been undergoing in 1960s and 1970s, main efforts in the field started from the second half of the 1980s.The literature of the optimization part is mainly categorized based on their solution approaches. White and Olson (White and Olson, 1986) use Linear Programming (LP) approach to optimize production target of the time horizon by dividing it into two separated but weakly coupled models from which the first one optimizes total operation including mine sector, plant sector and stockpile, and the second part maximizes the fleet production by minimizing total required volume to be handled. The model developed by Soumis et al. (1989) performs the upper stage in two steps. As the first step, it fixes shovels' location by implementing combinatory Mixed Integer Linear Programming (MILP) model with respect to available trucks and the objective of maximizing the production and subject to quality constraints. By solving the MILP model it suggests some location for shovels to be seated on the computer screen, and it needs a human to make a decision on the shovels sitting locations. Then after, as the second step of the algorithm Soumis et al. (1989) represents truck travel plan between shovels and dumping points by solving a Non-Linear Programming (NLP).

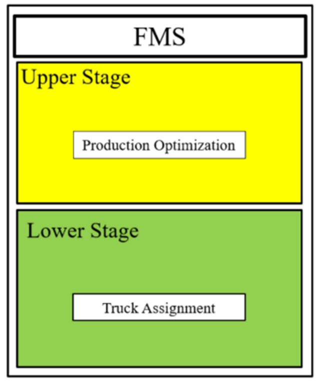

Fig. 2: A fleet management system

(Kappas and Yegulalp, 1991) offered a queuing theory model by considering truck – shovel system as a production network with regard to trucks as customer and shovels, crushers, waste dump, roads and maintenance service areas as servers. In their model, it is assumed that a mining system is a stochastic system with Markovian nature. Although it is stochastic, because of some parameters like service time distribution in different service areas, it is not Markovian (Newman et al., 2010).
Najor and Hagan (2006) applied queuing theory to analyze equipment (trucks and shovels) utilizations in the stochastic environment. Application of the model in an Australian case study shows that ignoring queue of trucks at hoppers (or plant capacity) causes overestimation of the production.

Later, Ercelebi and Bacetin (2009) represent a queuing theory model to allocate trucks in an open pit mine based on (Carmichael, 1987) which can estimate some of mining systems performance parameters including number of trucks, throughput of the processing plant and the waiting time.

After 2010, researchers mainly focused on implementing linear programming to solve the upper stage decision making problem in fleet management systems. Gurgur et al (2011) proposed an LP model of operation optimization that helps to minimize deviation of the operation from the strategically set targets in short- and long-term schedules. To link operational plan to the strategic ones the model provides shovel assignment. Ta et al. (2013) developed a mixed integer linear programming (MILP) model to allocate trucks of a fleet to different shovels based on probability of shovels' idle time. Mena et al. (2013) defined a knapsack problem which tries to maximize cumulative truck fleet production by a fixed time horizon. Chang et al. (2015) introduced an MILP model that schedules trucks over a shift by implementing MILP with the objective of maximizing transportation revenue. However, the models developed so far have some drawbacks as well. Main limitations of the existing fleet management systems can be highlighted as: Linkage to the strategic level short-term schedule, the impacts of drilling and blasting operations on the fleet operation, the effects of uncertainty and correlation of parameters governing the operation, Not accounting for the lost tons caused by mobility and equipment access problems particularly for shovels, The effects of the downstream active processes on the transportation operation, The impacts of the weather and traffic conditions on the shortest path between loaders and destinations, Optimum assignment of the shovels into the faces, Dynamic truck control, Incorporating mixed fleet systems (in most of the models). These limitations push models to result further from the real optimal decisions.

In this paper we develop a multi objective multi stage mining fleet management system that covers some of the aforementioned drawbacks of currently available systems. The developed fleet management system at its upper stage links operational plan of the mining operation to the mines short term plan or its production schedule by assigning the available shovels to the right polygons. At the same time it determines optimum path flow rate for each path connecting a loading point to a dumping location. Results of this step are being used in its lower stage to assign trucks to the right shovel by minimizing lost tons caused by equipment idle and wait times.

2. Models and Methods

2.1. Simulation Model

2.1.1. System

The system includes one open-pit mine, its haul network, its two processing plants and one waste dump. At the beginning of the operation, trucks are assigned and travel to a shovel from the bay. Then the loading process is done by the shovel. Afterwards, loaded material is transported to one of the destinations. As the next step in the system, the truck reaches the destination and backs up to the exact dumping location to dump the material. Here is the time dynamic programming part of fleet management system (FMS) finds the best truck among those just dumped their material into a dump and the trucks en route to a dumping point. At the same time, it finds the neediest shovel and matches the best truck with the neediest shovel. Then the truck travel to the shovel where dispatching system assigned it to. Another major optimization component of the system is the step three of the FMS that runs in a specific time intervals and whenever the system experiences a major change.

2.1.2. Key Performance Indicators

We have to define major Key Performance Indicators (KPIs) in order to evaluate systems' performance and asses the reliability of the models. Herein, what we are considering as KPIs are: total material input to each processing plant, tonnage of ore and waste material transported, stripping ratio, total amount of material transported, Loading time, Spot time, Dump time, Backing time, Empty and Loaded velocity of the trucks, and the utilization of the shovels.

2.1.3. Model inputs

The simulation model input can be illustrated within two categories of short-term schedule and the technical inputs. The required inputs from the first category are including: coordinates and node IDs for the digging locations, total tonnage of the blocks, material average grade for each block, ID of the destinations the materials are supposed to be sent to, Shovel number, sequence number for each shovel, precedence, and distances from the digging location to the dumping locations. The required technical inputs are: shovels' ID, bucket capacities, loading cycle time, availability, trucks' ID, number of trucks of each type, capacities, dump time, spot time, availability, average speed of trucks when empty and when loaded, backing time, desired grade of each material type at processing plants, maximum rate of processing at processing plants, geographical information regarding dumping locations, all information regarding coordinates of the nodes connecting different parts of the road network, information regarding activity of any paths within sources and destinations, bucket count for each combination of shovel type-truck type, and seasonal loading cycle times for each and every shovel type-truck type combination.

2.2. Optimization Models

2.2.1. Upper Stage Model Description

The upper stage of the model is formulated to provide shovel assignments and required path flow rates of trucks to the lower stage of FMS to comply with the short term plans and attain desired production and grades during mining operations. This stage uses a goal programming approach to optimize three objectives: 1) minimize the deviation in production, 2) minimize the deviation in tonnage of ore delivered to crushers, and 3) minimize the deviation in average grade delivered to crushers, as compared to maximum production, desired tonnage and desired grade at the crushers respectively. The problem is formulated as multi-period optimization model, where although the optimal decisions of the first period are passed on to the lower stage, the model solves the problem for multiple periods in the future and thus incorporates future requirements and state of the mine as well. The major set of constraints used in the model include: shovel assignment and movement constraints, material availability at faces, production capacity of shovels, production and grade constraints of the destinations, face precedence constraints and truck allocation constraints. Apart from these major constraints shovel failure constraints are also included to account for the dynamic mining system state. The model also incorporates shovel-material locking constraint to lock specific shovels to material if desired.

2.2.2. Lower Stage Model Description

The step four of the decision making procedure for FMSs to be implemented in any open pit mining operations working on the truck-shovel material handling bases is formulated considering three operational goals of the mining companies:

1. Maximize shovel utilization;
2. Minimize truck waiting time;
3. Minimize the deviation in the path flow rate compared to the desired flow rate.

A linear goal programming model has been formulated to optimize the goals.

First goal of the multi objective model represents total idle time for all the shovels working in the operation. The second goal of the model represents total truck waiting times for all the trucks available for assignment. And the last goal represents the difference between flow rate of the paths and the desired flow rates.
The multi objective truck assignment model is constrained by seven sets of limitations. The first set of constraints tries to balance truck rate at each shovel. It says that whatever truck goes to a shovel must leave the shovel as well. There exists another set of truck input balance constraint that governs the dumping location area. These constraints indicate that if any truck goes to a dumping location to dump its material, it must leave that location as well. Third set of constraints limit the system to make decision in a way that the operation is not allowed to use a truck more than its capacity that is called supply constraint. Besides, there is a set of demand constraints imposing the processing plants requirement to be met. Then, there are constraints governing deviations from the required path flow rate for each path. A set of non-negativity constraints limit variables to only accept non-negative values. Fig. 3 illustrate how any mining operation can talk to our developed multi objective multi stage fleet management system in a mining operation.

2.3. Optimization Model Solution Method

The Goal Programming (GP) was first introduced by Charnes and Cooper (1955) and (1961). In the simplest version of GP, the designer prepares some goals he or she wishes to achieve for each objective function. Then, the solving procedure will minimize deviations from the goals. This means that it does not maximize or minimize an specific objective, it tries to find an specific goal value of those objectives, though (Caramia and Dell'Olmo, 2008).

In the mining operation optimization there exist variety of goals to be achieved such as production maximization and maintenance of ore quality between the desired limits (Temeng et al., 1998), optimization of the processing plant utilization and minimization of trucks and shovels movement costs (Upadhyay and Askari-Nasab, 2015). In the former algorithm, the model maximizes shovel production and ensure ore grade requirement achieved as much as possible. The main advantage of GP model developed by (Temeng et al., 1998) is that it optimizes two major goals of the open pit operation simultaneously without neglecting any of them. Besides covering the objective function drawbacks of previous models it covers another disadvantage of LP models which is defining upper and lower limits for the target grade of material are being sent to the plant. As it was introduced before, in LP models it is usual to control the grade by imposing it between upper and lower limit. Let us assume that objective is to maximize the production. Then truck assignment to the shovel closer to the crusher which results shorter truck cycle time will be higher. If the average grade at these closer faces are pretty close to one of the allowed grade boundaries, then whatever the dispatching algorithm is controlling the feed grade within the interval is difficult. As a result, existing of stockpile and subsequently re-handling cost associated with it is undeniable. However, the model has some disadvantages. It does not consider all the goals are supposed to be met in an open pit mine operation such as equipment movement costs, of which some of them are covered by Upadhyay and Askari-Nasab (2015). The model the mining operation as a multi-period operation which needs to meet strategic goals of the project. It does not consider stochastic nature of the grade of material are feeding to the plant as well. The most recent open pit operation optimization model based on GP can be found in (Upadhyay and Askari-Nasab, 2015) where the authors enhanced aforementioned model's objective with adding two new goals. The newly added goals are minimizing the deviation of calculated plant feed to desire feed and minimizing cost of both trucks and shovels operation, respectively.

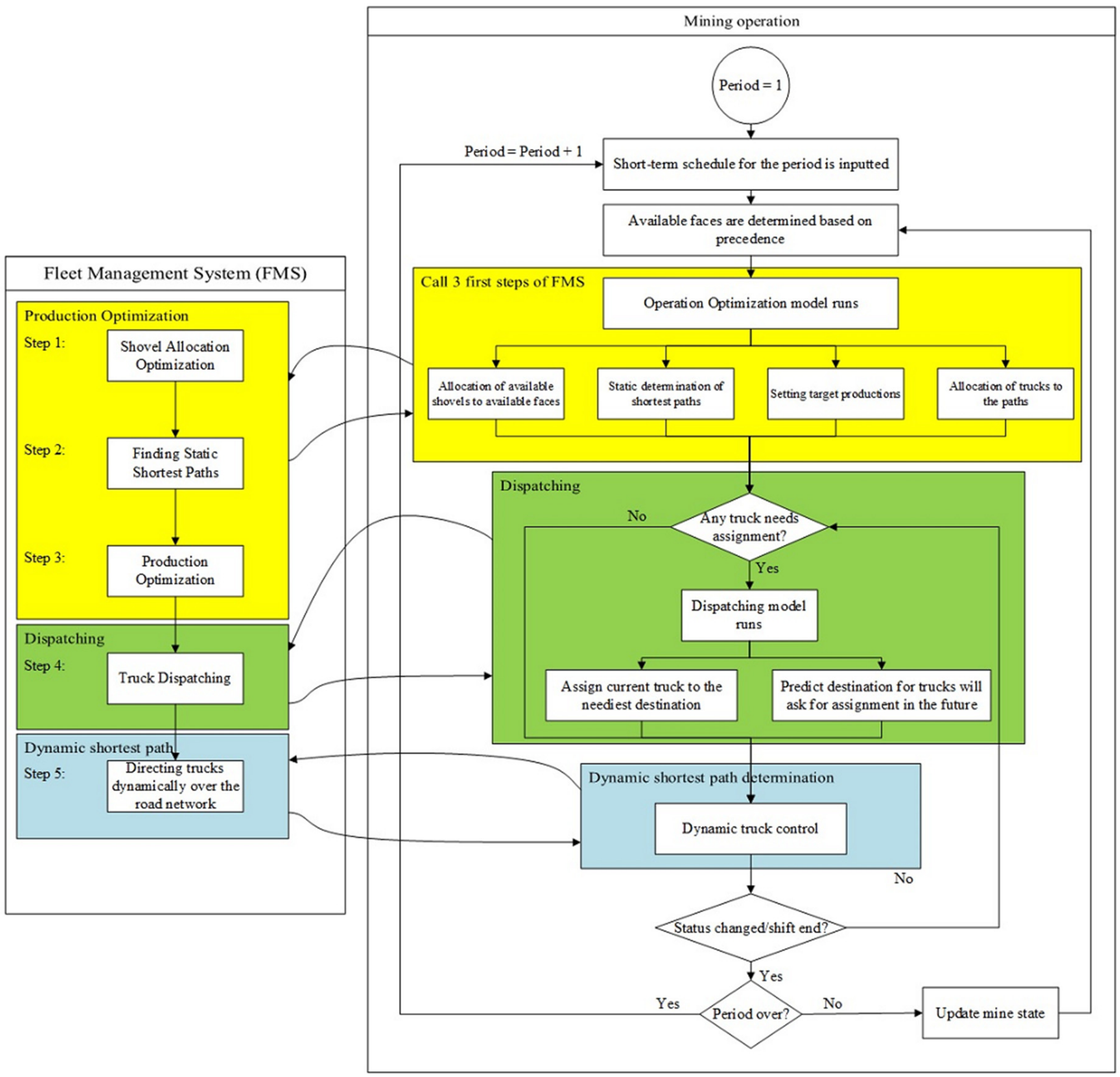

Fig. 3: Schematic representation of how the simulation model of a mining operation talks to the multi objective multi stage fleet management system we developed here.

Applying a non-preemptive goal programming approach the objective function of the truck assignment stage of the decision making process in the FMS is given by Eq.(1). A challenge here is that the goals are in different dimensions. To have a dimensionless objective function combining all the above mentioned goals it is necessary to normalize the goals. The normalization is done by determining Utopia and Nadir values for each and every goal. The normalized goals are multiplied by the weights to achieve desired priority and the final objective function obtained as Eq.(2).

$$\min Z = P_1\overline{G}_1 + P_2\overline{G}_2 + P_3\overline{G}_3 \tag{1}$$

Where:

$$\overline{G}_i = \frac{\left(G_i - z_i^U\right)}{\left(z_i^N - z_i^U\right)} \qquad i \in \{1,2,3\} \tag{2}$$

3. Case study– Gol-E-Gohar Iron Ore Mine

3.1. Mine Location and Its Operation Fleet

Gol-E-Gohar iron ore mine is located in Kerman Province of Iran. The project lies in southwest of the province, approximately 50 km southeast of the city of Sirjan (Fig. 4). Mining operation in Gol-E-Gohar is being handled by a truck shovel system. The operating fleet consists of Hitachi EX2500 and Hitachi EX5500 excavators and rigid frame rear dump Cat 785C and 793C trucks. There are three main dumping points for the loaded trucks including two processing plants and one waste dump each of which has two hoppers (or dumping point in the case of waste dump). Furthermore, Table 1 presents general specifications of the operating system. It is also worth noting that the mine operates for two 8 hours shift a day for 340 days a year.

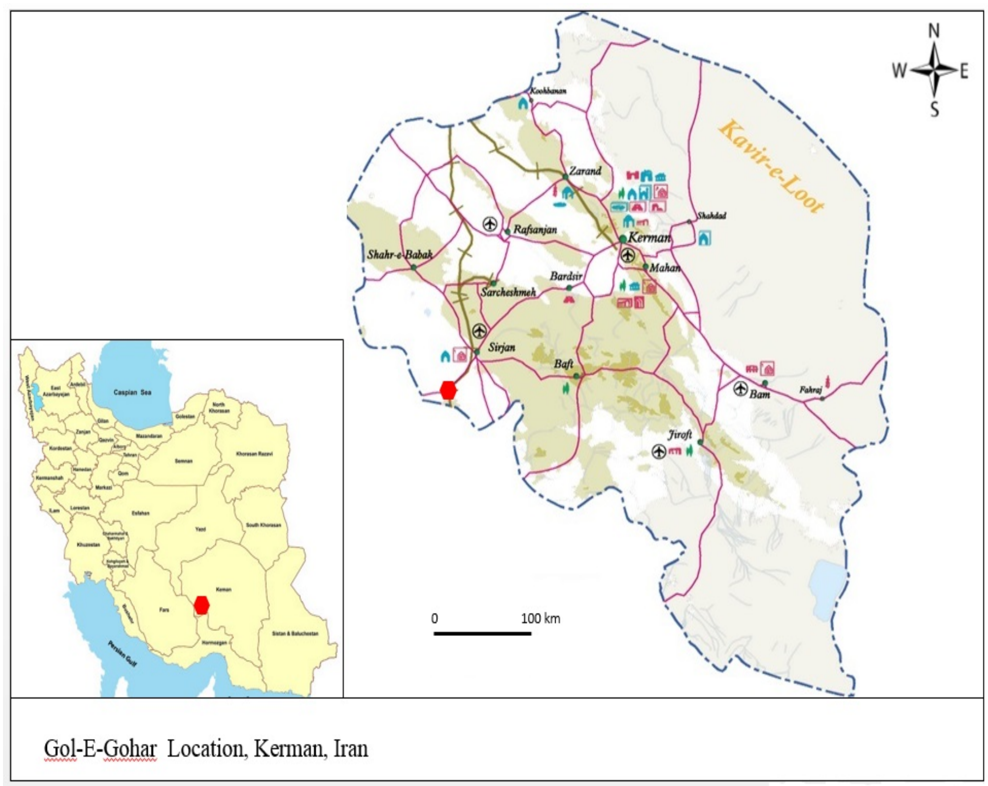

Fig. 4: Location of the Gol-E-Gohar Project in Kerman Province of Iran

Table 1: General specifications of the operation fleet

No.	Loading Point	Destination	Starting Distance (m)	Loader	Hauler
1	Shovel 1	Plant 1 Plant 2	4129 3626	Hitachi EX2500	Cat 785C & Cat 793C
2	Shovel 2	Plant 1 Plant 2	4196 3693	Hitachi EX2500	Cat 785C & Cat 793C
3	Shovel 3	Waste Dump	1930	Hitachi EX5500	Cat 785C & Cat 793C
4	Shovel 4	Waste Dump	1850	Hitachi EX5500	Cat 785C & Cat 793C
5	Shovel 5	Waste Dump	4295	Hitachi EX2500	Cat 785C & Cat 793C

3.2. Input parameters into the simulation model

Input parameters are required to run the simulation model. However, the values of these required input parameters are uncertain due to their nature. To account for the uncertainty of the parameters different distributions were fitted on the historical data from the database. Using Kolmogorov-Smirnov and Chi Square tests, the best function with the least square error from the empirical data was selected for each parameter. Fig. 5 represents the best fitted distributions on the dump time for both types of truck in the fleet tested by aforementioned tests. The main input parameter to be used in simulation model for what distribution fitting are required are: trucks spot time at each shovel, varies based on truck type and shovel type combination and mainly following Lognormal probability density function (PDF);number of passes required to load each truck type with a specific shovel type; loading cycle time for each shovel type loading a truck type, which changes based on types of equipment as well as change in season; amount of material each shovel type loads to a specific truck type in a single loading cycle; velocity of trucks in the mine road network when they are carrying material varying based on truck type; velocity of empty trucks, which varies based on truck type as well; duration of each truck type backing up at dumping points; and the time it takes for the trucks to dump their material into a dumping point varying based on truck type. Table 2 introduces the best fitted models on some of the aforementioned parameters to be used in the simulation.

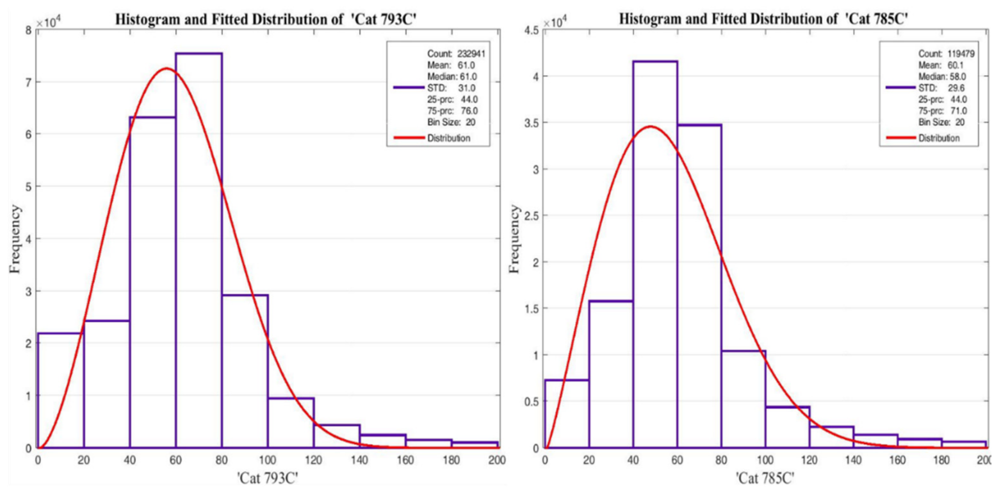

Fig. 5: Best fitted distributions on dump time to be used as input parameter in simulation: a) time (seconds) it takes Cat 785C to dump its loaded material; b) Cat 793C dump time (seconds)

4. Results and Discussions

In this section, we measure previously defined key performance indicators in the simulation model of the case study to illustrate performance of our developed system. To do so, we developed a linkage between the developed fleet management system and simulation model of the case study.

Table 2: Summary of some of the input parameters best fitted distribution

Data set	Truck & Shovel combination	Best fitted distribution
Spot time(s)	Hitachi EX2500 & Cat 785C	LOGN(32.7, 26.5)
	Hitachi EX2500 & Cat 793C	LOGN(42.4, 41.4)
	Hitachi EX5500 & Cat 785C	LOGN(69.7, 94.6)
	Hitachi EX5500 & Cat 793C	LOGN(79, 114)
Winter loading cycle time(s)	Hitachi EX2500 & Cat 785C	NORM(17.1, 0.526)
	Hitachi EX2500 & Cat 793C	TRIA(16.6, 18, 18)
	Hitachi EX5500 & Cat 785C	NORM(16.5, 0.99)
	Hitachi EX5500 & Cat 793C	16.6 + ERLA(0.254, 3)
Loaded velocity (km/hr)	Cat 785C	3.6 + GAMM(10.04, 22.79)
	Cat 793C	1.06 + LOGN(18.64, 7.56)
Dumping time(s)	Cat 785C	NORM(60.1, 27.9)
	Cat 793C	NORM(62.7, 28.7)

4.1. Linking the fleet management system to the simulation model

A fleet management system is a tool that is used to make required decisions over the operation. The decisions to be made must be as close to optimality as possible. Thus, the system needs to solve an optimization model for each decision to be made. To solve these optimization models fleet management system needs an external optimization solver that is linked to the simulation model. Each time a decision is to be made, required input data from the simulation model are written into an external file. And then, using a linker, the simulation model recalls the fleet management system to make decision based on the provided data. At this time, fleet management system solves the decision making problem using an external optimization software and report the results to the simulation model.

In this study, fleet management system is linked to the simulation model using two linkers. Fig. 6 illustrates how the simulation model is linked to the fleet management system.

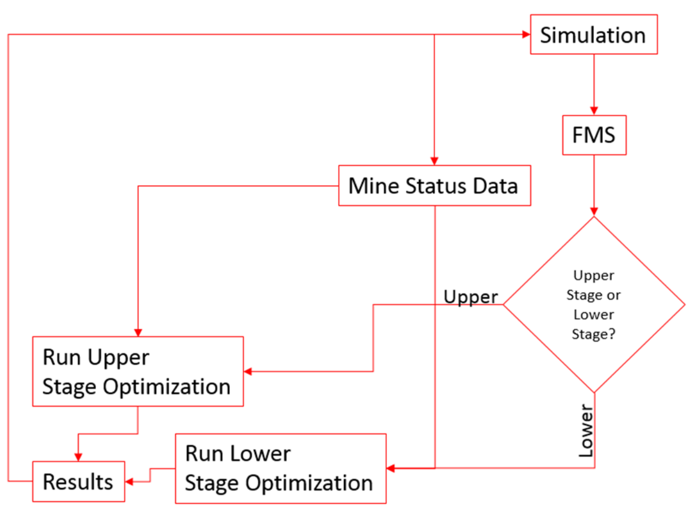

Fig. 6: Linkage between simulation of the mining operation and the fleet management system

4.2. Simulation Run Setup

We ran the simulation and optimization model of the case study for five replications in Rockwell Arena (Rockwell Automation, 2016) software linked to MATLAB R2016a (Mathworks, 2017), and CPLEX (IBM, 2016) for 37 Cat 785C truck type over 10 days of operation with 2 shifts per day. The operation is running for 8 hours per shift. Uncertainties associated with all the input parameters are being accounted for using statistical distributions.

After running the model for the replication length of 160 hours, the results of the study exported to a database and post processing of the data has been done. The results are presented in following subsections.

4.3. Production Schedule

Simulation study shows that managing the mining operation fleet for the case study using developed fleet management system will help the operation to meet the short term schedule requirement as shown in Fig. 7.

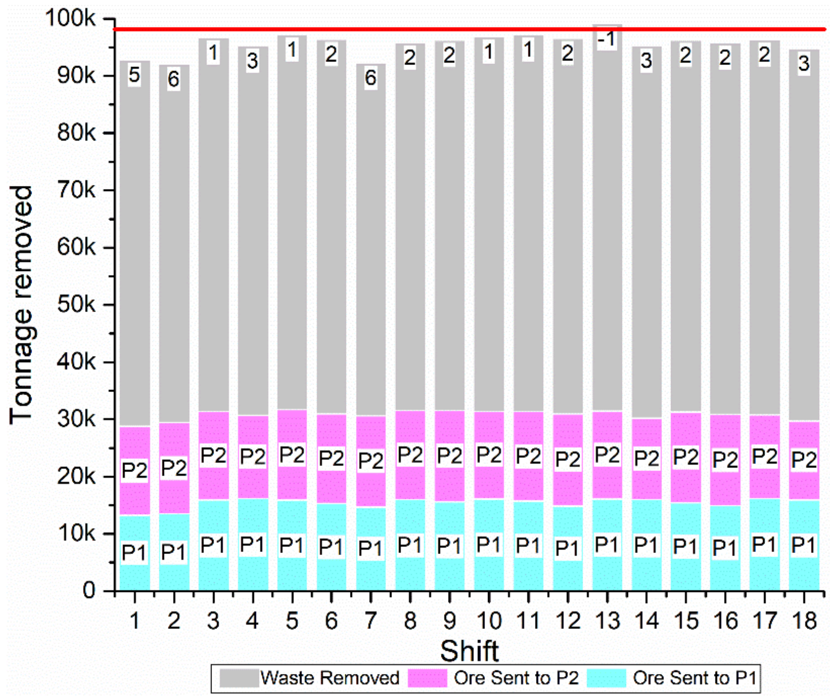

Fig. 7: Shift by shift production schedule met by the operation using developed fleet management system (numbers on the top of each bar shows shift production deviation from the desired production and the red line is the required production per shift).

Fig. 7 shows that by implementing the developed multi objective multi step mining fleet management system, the short term schedule of the operation is met with an average of 2% deviation. To be able to analyze the material sent to each processing plant more precisely, Fig. 8 and Fig. 9 illustrate how desired feed rate for each processing unit is met by implementing the multi objective multi stage fleet management system.

It is depicted in Fig. 8 that despite two first shifts of the operation that need to be reconsidered in the future works, in the simulation model of the case's operation the multi objective multi stage fleet management system meets plant 1 desired feed rate with an average deviation of 2%. However, this deviation from plant required feed rate for each shift is a bit higher in the case of processing plant 2.

Fig. 9 shows that implementing the developed fleet management system in the case study operation results in an average of 4% deviation from plant 2 desired feed rate.

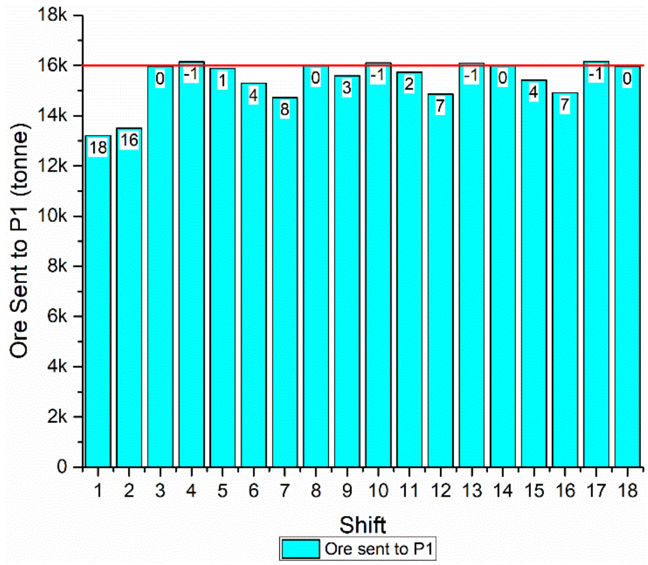

Fig. 8: Ore sent to processing plant 1 in each shift (number on the top of each bar shows percentage deviation from the desired feed per shift (red line))

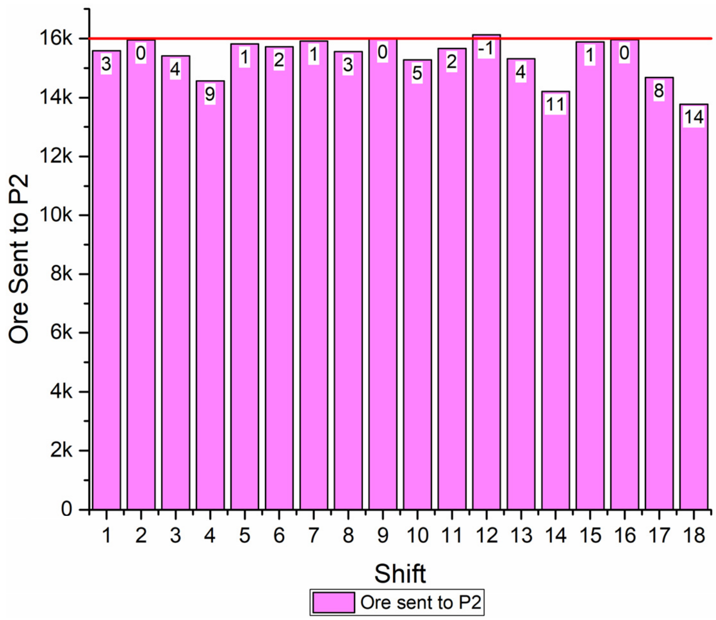

Fig. 9: Ore sent to processing plant 2 in each shift (number on the top of each bar shows percentage deviation from the desired feed per shift (red line)).

4.4. KPIs measurement

4.4.1. Plant Head Grade

As it was mentioned above, the mining operation has two active processing plants. Each of these plants has its own average, lower limit, and upper limit for head grade of material sent to them in hourly bases. Table 3 lists the acceptable range for the grade of material to be sent to each of the plants.

Results exported from the simulation output database show that hourly head grade requirement for both of the active processing plants have been met by the FMS developed hear in this research. Fig. 10 represents hourly head grade for the material fed to each of the plants over simulation running time. It is shown that for both of the plants feed grades are fallen into the acceptable range around desired average head grade.

Table 3: Acceptable range for grade of material to be sent to the plants per hour

Plant	Lower Bound of Head Grade	Average Head Grade	Upper Bound of Head Grade
Plant 1	60%	65%	70%
Plant 2	70%	75%	80%

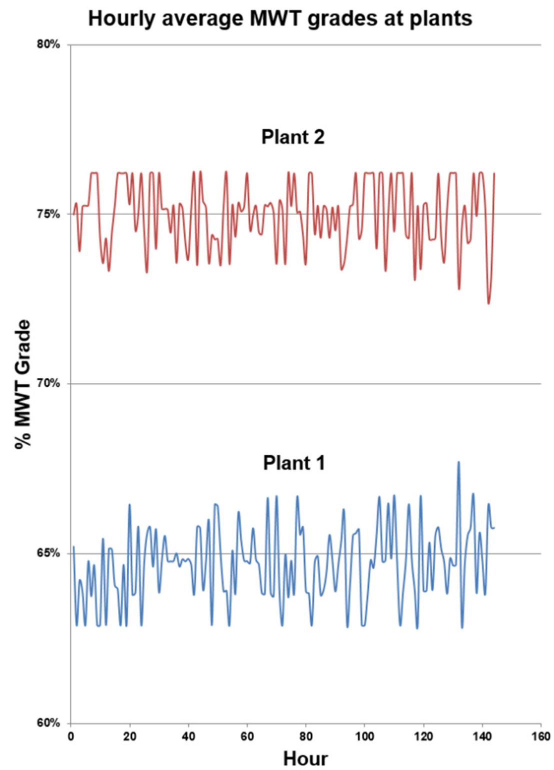

Fig. 10: Hourly plant head grade met by the FMS over 160 hours of the mining operation.

4.4.2. Plant Feed Rate

Another important KPI to be tracked in each mining operation is the tonnage of input to each processing plant. Hear in the described case study each of the processing plants need to be fed of around 2000 tonnes per hour. Fig. 11 and Fig. 12 show histogram of hourly input to plant 1 and plant 2 of the operation, respectively.

According to Fig. 11 the fleet management system allocates equipment semi-dynamically and assign them dynamically in a way that the plant 1 feed rate is met with a deviation of the mean of less than 2%. The model is delivering an average of 1935 tonnes per hour to plant 1 with a standard deviation of 190 tonnes. The same conclusion can be extracted from Fig. 12 regarding plant 2 feed rate. Fig. 12 indicates that plant 2 desired hourly feed rate is met with a deviation of the mean of less than 3% by implementation of the multi objective multi step fleet management system. As shown in Fig. 12 the fleet management system is able to make decisions resulting in delivering an average of 1930 tonnes per hour to plant 2 with a standard deviation of 190 tonnes. This proves that the operation will meet the goals of strategic plans and it will be able to satisfy the predicted market to a very good extent.

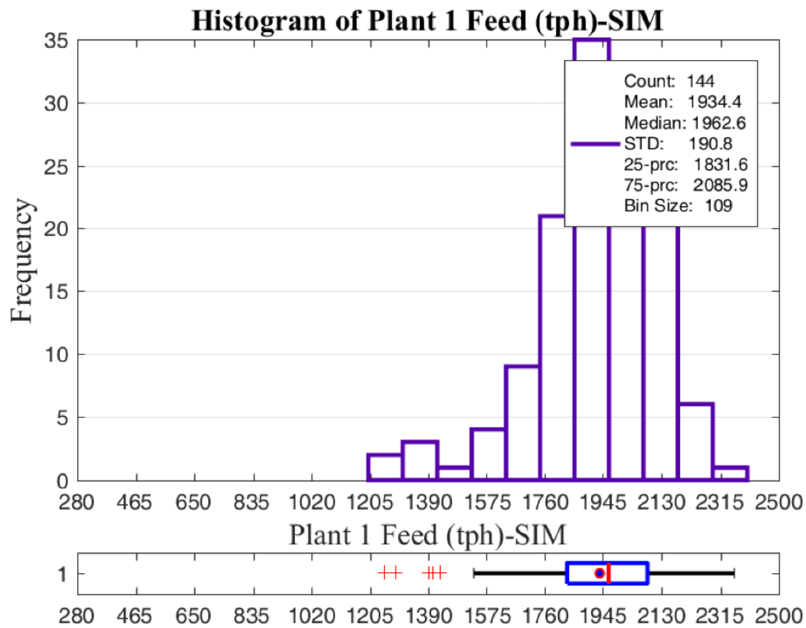

Fig. 11: Histogram of plant 1 hourly feed rate

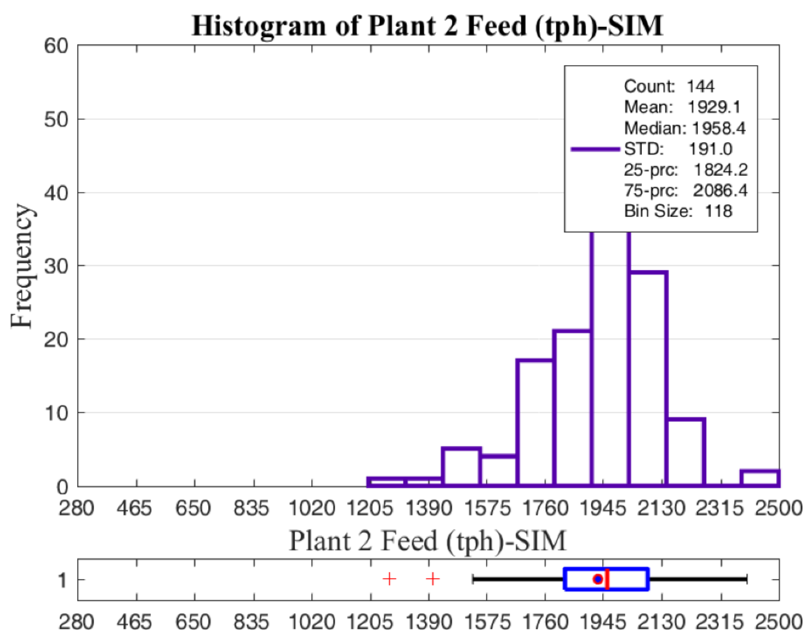

Fig. 12: Histogram of Plant 2 hourly feed rate

4.4.3. Queue at Origin and Destination Points

Queue of the trucks at loading or dumping points suggests inefficient use of the truck fleet, which may even result in production loss. So the fleet size for a mining operation is determined to be the smallest possible fleet size that is capable to meet the production requirements. However, losing some times in queues either at shovels or at dumps cause production losses. As a result, to overcome these production losses the operation will require a fleet size larger than its optimum fleet size. Thus, having a shorter queue length at both origin and destination points will help the operation to have less production losses and as a result to need smaller fleet size. One of the major advantages of the multi objective multi stage fleet management system developed hear is that it tries to minimize queue length. Fig. 13 and Fig. 14 illustrate statistical summary and histogram of the queue length at dumping points and loading areas when implementing the developed multi objective multi stage fleet management system to make decision in the case study's operation, respectively. It is worth noting that the histograms are plotting over the times there was a queue at the point. It means that all the queue lengths equal to zero were excluded from the histograms and the statistical results. Statistical analysis of the queue at dumping locations show that if any happens, an average of 1.7 trucks line up at dump locations with a median of 1 truck. Regarding queue length at shovel, the statistical data analysis and the histogram presented in Fig. 14 show that decisions made by the developed fleet management system causes an average of 1.8 trucks line up in queue at shovels with a standard deviation of 1 (if any queue happens at any shovel).

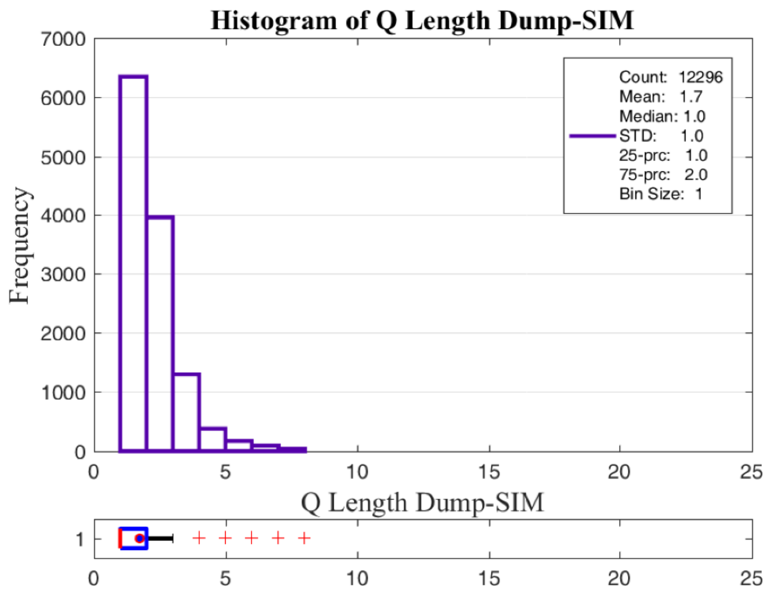

Fig. 13: Histogram of queue length at dumping locations (queue lengths of zero are excluded).

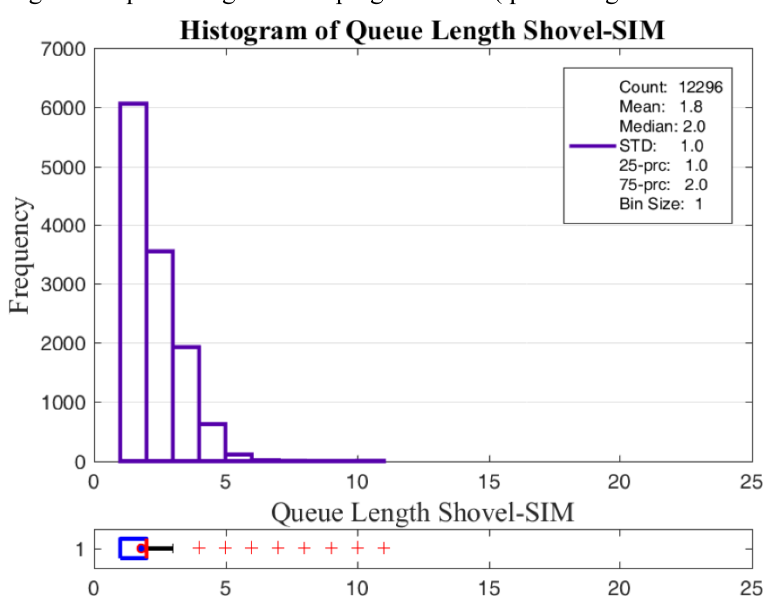

Fig. 14: histogram of queue length at loading points (queue lengths of zero are excluded).

5. Conclusions

A multi objective multi stage mining fleet management system that has capability of making operational decisions in open pit or any surface mining operation was developed and introduced in this paper. The developed fleet management system has number of advantages over the currently available systems. The main advantage of the developed system is that it minimizes the human intervention in both production optimization and truck dispatching steps. By making optimal decision on the shovel assignment to the available faces it links mining operation to the strategic plans of the mine. Besides, after running a multi objective decision making model for production optimization step by the time any kind of big change happens, it decides on trucks next destinations whenever any truck asks for new assignment. The truck assignment optimization model is coupled to and follow the production goals imposed by upper stages and minimizes deviation from them. It is also capable of maximizing productivity of both the transportation equipment and loading units. Another advantage of the developed fleet management system over currently available systems is that no matter how many trucks require assignment at the moment, the system dispatches them in an optimum way. To verify the developed fleet management system it was linked to a simulation model of a mining operation and the result of the simulation study are presented in this paper. The results show that the scheduled production of the mine's strategic plan is followed by the decisions made using the multi objective multi stage mining fleet management system developed in this study with less than 4% deviation.

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Strategic Evaluation of Mineralized Waste Rocks as Future Resource

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ABSTRACT

Current mining practices do not extract all mineralized rocks due to the present mine planning concept of economic resource depletion as opposed to physical resource depletion. Improvement in factors including mineral prices and processing recovery could potentially make mineralized waste rocks profitable. This paper discusses the management of mineralized waste rocks as future resource, and further proposes a framework that maximizes the benefits of mining and processing mineralized waste rocks. A gold deposit was used as case study to evaluate the conventional and proposed waste rock management practices. Future gold prices were modeled using Fourier analysis while technological advancement in gold processing recovery were deduced from historical and current trends. The evaluation was based on the net present value (NPV), life of mine (LoM), internal rate of return (IRR), cashflow, resource depletion ratios and payback periods. The potential simultaneous increase in future gold prices and processing recovery (Scenario 3) was the option with the best performance. Implementation of Scenario 3 will deplete the mineral resource by 92.3%, compared to 59.5% depletion ratio by the conventional practice. The estimated NPV and LoM of Scenario 3 increased by 12.6% and 82.9% respectively, compared to the conventional practice. A well-integrated mining strategy that focuses on both economic and physical resource depletion is vital to the management of mineral resources for economic, social and governmental benefits of a country. Policy and technical reforms have been recommended to encourage mining companies to consider the proposed mineralized waste rocks management framework in their long term strategic mine plans.

1. Introduction

As mineral commodities have become a form of currency, whether for trade or sale in this growing technological and industrial economy, the need and value for metals and minerals have significantly increased. The dependence on mining to produce large amounts of these minerals to meet current needs have resulted in the processing of high volumes of mineralized material and subsequently producing huge amounts of waste rocks and processing plant tailings (Lottermoser, 2010). Thus, the convention, "if it cannot be grown, it has to be mined", will have severe notable drawbacks mostly because of the depleting nature of finite mineral resources on the planet leading to sustainability challenges on the management of mineral resources.

In the mining industry, not all mineralized rock is profitable for extraction and subsequent processing under the current economic regime, available processing techniques and technological constraints. Lottermoser (2010) noted that, extraction and processing techniques used in the past were less efficient, and resulted in mine wastes of significantly high mineral contents. The term "mine waste" is used to categorize the material that is extracted from the ground with no current

This paper was submitted to the International Journal for Mining, Reclamation and Environment in September, 2017

economic value, and is thus stored or discarded rather than processed. Similarly, "mineralized mine waste" refers to the category of rock material containing some percentage quantities of mineral content with future potential economic benefits. In their current form, mineralized waste rocks are not profitable based on current economics, available processing techniques, technological constraints and governmental policies.

In recent times, mining of material previously defined as waste for older mines is very common. These mining operations require less energy in extraction and transportation for reprocessing and/or recycling (Lottermoser, 2011). It is interesting to note that, the traditional mining and waste rock management practices do not accommodate the concept where waste material potentially become mineral resources for future generations. The traditional mining model where the easiest, most profitable minerals are mined first, leaving the lower grades or difficult-to-process materials in-situ or transported to waste dumps needs to be modified. The changes will promote the sustainability of the mining industry and create opportunities to harness the full benefit of the mineral resources. For natural resources that are essentially non-renewable, the conventional mining approach needs to be re-evaluated. This will be the beginning of the revolution to the old convention of mining where economic depletion of mineral resources is preferred to physical depletion.

This paper evaluates the current traditional mining and waste rock management system, and further proposes an innovative approach for mining and waste rock management that considers mineralized waste rock as potential future mineral resource. Using GEOVIA GEMS and Whittle software (GEOVIA-Dassault, 2015, 2014), a conceptual framework for mine waste management system that ensures future processing of mineralized waste rock has been evaluated with real data from two mining companies in Canada. The results of the study together with legislative requirements have been discussed. Recommendations on resource policy reforms and modifications to the management of mine waste rocks as a potential future resource have been proposed.

1.1. Mineral resource depletion

Current general mining practices aim at maximizing the net present value for the operation by mining the easier to access and higher grade minerals first while leaving the more difficult and lower grade minerals in-situ or sent to waste dumps. Mineralized waste rocks are mined to uncover the ore blocks underlying such waste rocks. These mineralized waste rocks are sent to waste dumps which end up mixing with the non-mineralized waste rocks. This conventional waste rock management method results in the loss of future potential mineral resource and sustainability issues due to the progressive peak mineral requirement paradigm and growing mineral consumption. Sustainability refers to the continuous development in areas including physical expansion, social, environmental and economic development of mineral resources. However, unsustainable practices lead to numerous challenges such as land degradation and resource depletion. Mineral resource depletion has been a concern for most researchers in resource sustainability (Gordon et al., 2006; Tilton and Lagos, 2007; Giurco et al., 2010). Discussions about the mechanism of resource depletion have deepened with researchers finding solutions to questions such as "will previously categorized waste rock materials be mined when commodity prices increases and/or mining technology advances?" (Willett, 2002; Giurco et al., 2010; Prior et al., 2012). Tilton and Lagos (2007) however maintained that the fixed stock paradigm is not representative of the actual availability of resources but instead, an opportunity-cost paradigm is more representative of actual resource availability.

In terms of resource sustainability, it has been argued that it is better to continuously prolong the extraction of existing mines than opening newer mines as long as the mining operation is still productive and economic within sustainability dimensions (Weber, 2005; Laurence, 2011). Many issues such as land degradation and resource depletion from current unsustainable practices look to pose problems for future generations. In order to remedy the situation, research into waste recycling is rising in importance (Lottermoser, 2011), and the concept "sustainability does not mean zero growth" (Meadows et al.) is gradually being advocated.

The "Prophesies of Scarcity" suggests that there is a response to the depletion of both renewable and non-renewable resources (Williamson, 1945). Giurco et al. (2010) proposed that resource depletion models are indications that resource management should be more integrated in the planning phases. Although resource management concepts have mostly been researched in fields of renewable resources such as fisheries and forestry, it has barely been discussed as a critical concept in the fields of non-renewable resources. Efforts that were previously focused on non-renewable resource depletion analysis have been hindered in the last two decades (Giurco et al., 2010). Due to the expansion of the mining industry resulting from discoveries of several large mineral resources, advances in processing technology, better techniques of mining and increases in commodity prices; focusing on the concept of physical depletion as opposed to economic depletion of mineral resources must be strategic.

In recent times, discussions on resource governance and how nations can maximize resource benefits have increased. For instance, the Alberta Energy Regulator (AER) has established criteria that define the mining cut-off grade and minimum processing plant recovery factor. According to Directive 082 by the AER (Ellis, 2016), the criteria seek to ensure conservation and further prevent sterilization of oil sands resources in the Province of Alberta, Canada. The criteria outline that:

a) The in-situ oil sands cut-off grade, defined as the minimum bitumen content of oil sands ore, must be 7 weights per cent bitumen; and

b) The processing plant recovery is a variable factor based on the average bitumen content of the as-mined ore. The factor is determined as follows:

   − If the average bitumen content of the as-mined ore is 11 weights per cent bitumen or greater, the recovery factor is 90 weights per cent.

   − If the average bitumen content of the as-mined ore is less than 11 weights per cent bitumen, recovery is determined by Equation (1), where x is the average weight per cent bitumen content of the as-mined ore:

$$\text{Recovery} = -202.7 + 54.1(x) - 2.5(x^2) \qquad (1)$$

1.2. Large volume waste management

In the mining industry, development of essential technologies including flotation, new methods of pyrometallurgy, geophysics, drilling practices and machinery have improved the extraction techniques and technologies over the past 50 years (Gordon et al., 2006). Large volume waste often refers to waste rock and/or tailings generated during the mining and processing operations of a typical mine. The mine waste management hierarchy in Fig. 1 is a well-established guide for prioritizing waste management practices, showing most favored approach at the top to least favored approach at the bottom. As presented in Fig. 1, minimization of mine waste is the most preferred option, whereas treatment, disposal and storage are the least preferred options. Reuse and recycling is amongst the top feasible options in waste management (Lottermoser, 2011). However, the most common practice used in conventional mining and waste management is the treatment, disposal and storage options.

Technological advancements in the mining industry potentially improve the economic value of mineral deposits. These advancements lead to efficiencies in milling and refining processes that invariably increases the potential extraction of minerals in mining operations (Hatayama et al., 2014). Mineralized mine waste may not necessarily be completely worthless, but rather not profitable under the current economic or technological conditions. These materials often contain valuable mineralization that can be potentially extracted in the future. As extraction economics and technologies improve, materials that were previously considered waste can be processed. Furthermore, as commodity demand and price increases, the need for innovative technologies and reprocessing will also increase. This will result in further research efforts on these subjects.

The recycling and processing, as well as miscellaneous reuse of mine wastes (such as fill for roads, reclamations, etc.) are done for both financial return as well as convenience. With the increasing demand for minerals and materials in the global market, the recovery of valuable minerals and reuse of waste rock materials are becoming increasingly important and enticing (Lottermoser, 2011). In the past, gold recovery efficiencies were in the ranges of 35% to 60%, depending on the ore properties and extraction techniques (Eissler, 1896). Based on recent technological advances in recovery techniques, most previously abandoned mineralized mine waste are potential resources for reprocessing.

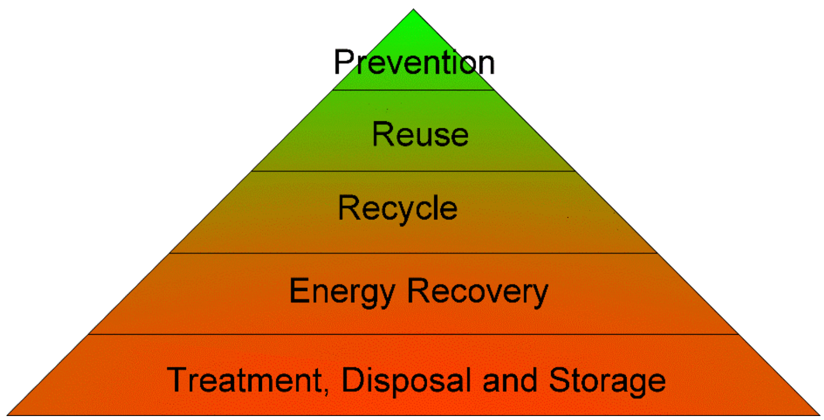

Fig. 1: Mine waste management hierarchy modified after Lottermoser (2011)

1.3. Current mining and waste management practices

Waste in mining is categorized as rock materials that are not economical to process at the time of extraction or the byproduct effluent from the processing and refining of ore materials usually deposited at the tailings impoundment. These waste dumps or containment facilities often require very large geographic footprint for their management. Because of this, the long-term impacts of these waste facilities require extra attention during the design and mining phase bearing in mind that the extent of hydrological systems in waste storages are not fully understood (Mining, Minerals and Sustainable Development (MMSD), 2002). Fig. 2 is a representation of waste management in current mining practices.

It can be seen that the waste dumps and tailings impoundments are not usually considered to have opportunities for future reprocessing as part of the long term waste management of the mine (Dold, 2008). Typical mining companies transport any rock material containing minerals below the cut-off grade to the waste dumps. Thus, non-mineralized and mineralized waste rock materials containing minerals lower than the cut-off grade but required to be mined to gain access to blocks of higher grades are dumped together on the waste pad. Occasionally, these mineralized and non-mineralized waste rocks are used to backfill voids or valleys, for road and civil constructions, and as backfill materials during pit reclamation.

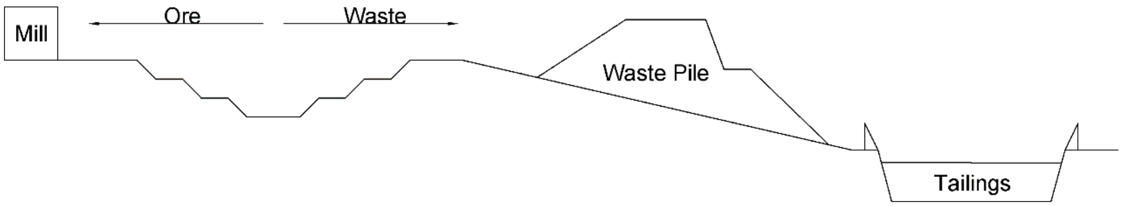

Fig. 2: Current mining and processing scheme modified after Dold (2008)

A typical mining company such as Sankofa Gold Limited in Ghana currently mines and processes the low grade materials (tailings and mine waste rock) of the former Prestea Goldfields Ltd – a previously active underground mine (Gbireh et al., 2007). After several years of closure of this underground mine, it has been reopened and is being operated by Golden Star Resources, Prestea Mines (Zhang et al., 2015; Brakopowers, 2016). Perseus Mining (Ghana) Limited has fully explored and is currently mining an abandoned old mining pit that was backfilled by AngloGold Company Limited several years ago (Amegbey et al., 2016). AngloGold Ashanti Obuasi Mine has completed the re-mining of its Diawuso tailings in 2015 (AngloGoldAshanti, 2015). Such reopening of old mines and re-mining of mineralized waste rocks was not managed as potential future mineral resource. The Mount Morgan mining operations (Carbide Resources, 2015), is also another gold and copper mine located in Queensland, Australia, that is being reworked after several years of abandoning of the mining site.

These historical information supports the fact that, if mine management had potentially mined the mineralized waste rocks and stockpiled them for the future, there would have been maximum exploitation and recovery of the existing mineral resources of that region. Furthermore, current environmental and social impacts of these abandoned mineralized waste rock and the preparation of these abandoned mines for mining in their current form would be avoided.

1.4. Proposed mining and waste management practices

Based on the rate at which resources are being consumed, the world will require more resources than available on Earth in this century (Meadows et al., 2005). Fig. 3 shows the continuous upward trend in the number of Earths required to provide the needed resources for man's use and to absorb the associated emissions per year since 1960. Between 1975 and 1980, humanity exceeded the capacity of the earth to sustain our current activities, requiring change in practices to remedy the situation.

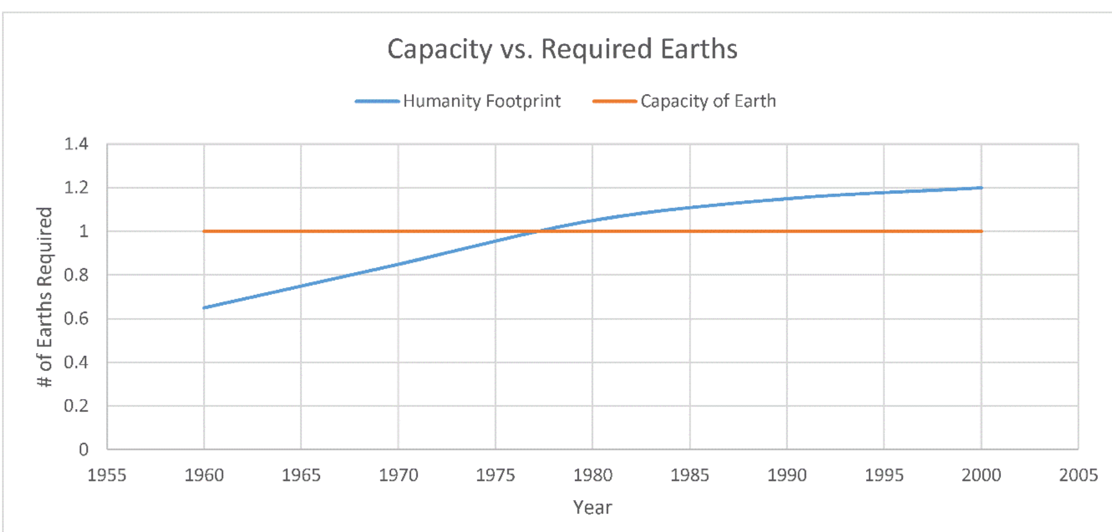

Fig. 3: Footprint vs. earths required for sustainability modified after Meadows et al. (2005)

Current mineralized waste rocks can be used as a future resource in times of commodity scarcity (Lottermoser, 2011), technological advancement and, improvements to mining and processing techniques. Managing the mineralized waste rock as future resource, coupled with existing environmental consciousness will reduce the mining footprint and negative social impacts. Fig. 4 shows the proposed mining and mineralized waste management framework modelled after (Dold, 2008). Due to favorable conditions of possible commodity price increase and/or cost reduction, as well as technological advancement to increase recoveries in the future, the potential return on investment and mine life increases. Fig. 5 shows a simplified schematic of the return on investment as mine life increases due to the implementation of the proposed system. This shows the profit profiles and extension of mine life compared to the conventional mining system.

The basic concept of the proposed framework is to ensure that as much as possible, the existing mineral resources are physically depleted as opposed to economic depletion. Fig. 6 shows the conceptual framework used to model the various mining and waste management scenarios that allow for future reprocessing of mineralized waste rocks compared to existing conventional practice. The framework is used as a basis to develop and simulate with mine data, two case studies to determine the feasibility of the proposed extensive mining and waste management system.

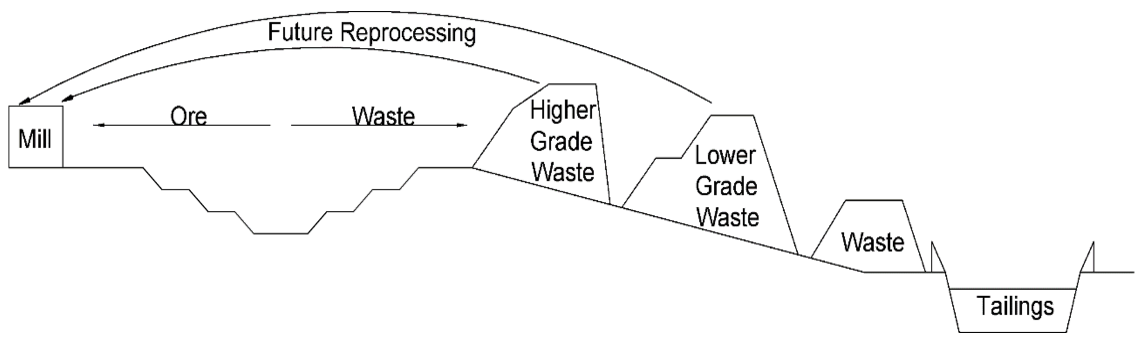

Fig. 4: Proposed waste management scheme for future reprocessing of mineralized wastes modified after Dold (2008)

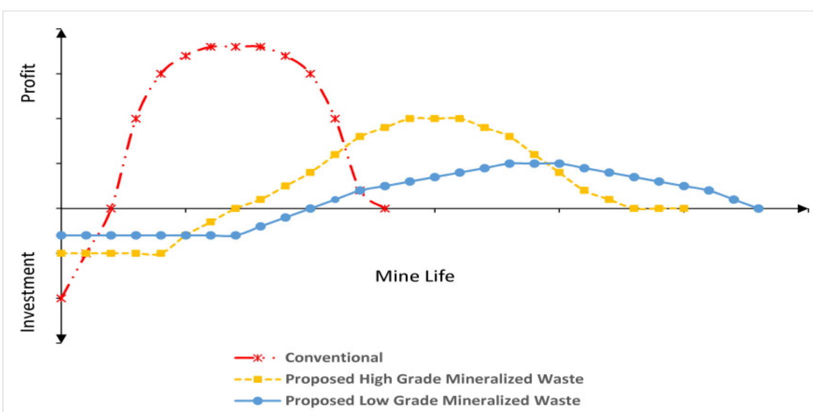

Fig. 5: Visual representation of value of proposed waste management system modified after Dold (2008)

Case Study 1 highlights the conventional mining practice with current mineral price and processing technology as exist in most mining operations today. Case Study 2 depicts the proposed mining and waste management practice which features future mineral price increase and processing technology advancements for an extended mining operation. For simplification, it was assumed in Case Study 2 that all other future mining economics data remain the same.

Using the current and forecasted economic, mining and processing data for similar gold mines in Canada, three scenarios of the proposed framework (Case Study 2) were evaluated and compared to the results of the conventional mining practice (Case Study 1). These scenarios were based on:

1) future increase in mineral price; 2) future technological advancement; and 3) future technological advancement and increase in mineral price. The comparison was made on the estimated total revenue, overall life of mine, internal rate of return (IRR) and payback period; while ensuring physical depletion of the mineral resources to promote sustainable mining.

Due to a potential increase in future price of the mineral, the first scenario evaluates the feasibility of mining and processing mineralized waste rock previously categorized as materials below the established “cut-off grade” per the current economic conditions. The second scenario evaluates the feasibility of mining and processing mineralized waste rock based on the effect of future technological advancement in processing (thus, processing recovery improvement) of the mineralized waste rock. The third scenario evaluates the economic potentials of mining and reprocessing mineralized waste rock in the future when both processing technology advances and mineral prices increase in the future. This third scenario is the “best case” scenario for future mining and processing of mineralized wastes.

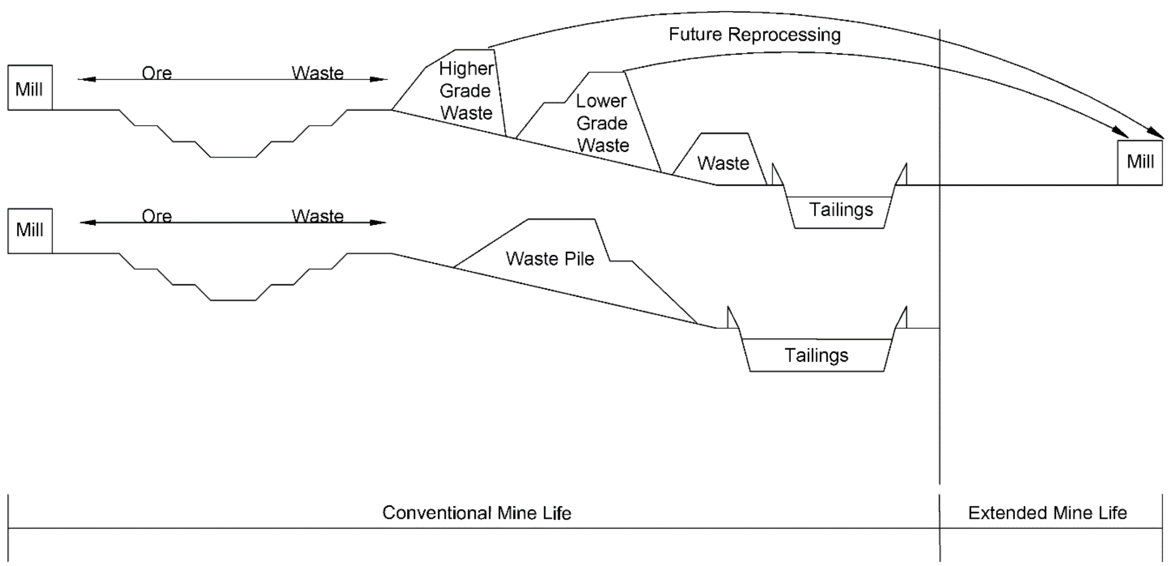

Fig. 6: Mine life impact of sustainable waste management systems

2. Quantitative evaluation

2.1. Brief description of orebody

The gold (Au) deposit in the case study is very shallow and uniform with an average grade of 1.73 g/t and spans an approximate area of 1.0 km^2. The mineral resource was estimated in GEOVIA GEMS 6.7.3 and contains a total of 98.7 Mt of mineralized rock. With a cut-off grade of 0.5 g/t, 76.2 Mt of mineralized rock at an average grade of 1.8g/t was categorized as ore while 20.5 Mt of the resource with an average grade of 0.28 g/t was categorized as mineralized waste. Using the economic data provided in Table 1, the optimum pit was generated with GEOVIA WHITTLE 4.6 (GEOVIA-Dassault, 2015).

2.2. Current economic data

Current economic data on mining and milling operations were garnered and used as basis for the evaluation of the current conventional mining and waste management practices, and the three scenarios of the proposed mining and waste management framework. These economic data were averaged from two Canadian open pit gold mines feasibility reports. The data include mining and processing costs, general and administrative costs and, capital and closure costs. The current Au price used for the evaluation is C$ 1,600 (USD$ 1,165). The current economic data including the estimated operating and capital costs are presented in Table 1.

Table 1: Average capital and operating costs from two open pit gold mines in Canada

Capital and Operating Costs	Values
Mining Costs (C$/tonne)	5.39
Processing Costs (C$/tonne)	8.93
G&A Costs (C$/tonne)	1.59
Selling Cost (C$/Oz)	53.57
Re-handling Cost (C$/tonne)	0.50
Total Cost (C$/tonne)	16.45
Initial Capital Costs (C$M)	740.00
Closure Capital Costs (C$M)	250.00
Total Capital Costs (C$M)	980.35

2.3. Mineral price forecast data

Historically, gold price has remained fairly constant over a century from 1833 to 1968 before it started to fluctuate (Macrotrends, 2016). A 50-year historical data on gold price from 1966 to 2016 (Macrotrends, 2016) was used in generating a model for predicting future gold prices. Future gold prices have been modeled by researchers based on several factors including gold demand and supply dynamics, oil prices, international inflation, devaluation of the US dollar versus other currencies, prosperity of world economics and international political environment. Some of the tools and techniques used to model the future prices of gold include simple statistical approach, application of neural networks, diffusion models, nonlinear models, time-series forecasting methods and inferences (Grudnitski and Osburn, 1993; Hadavandi et al., 2010; Shafee and Topal, 2010; Fumi et al., 2013; Makridou et al., 2013; Li, 2014).

Using the 50-year historic data, a single trend Fourier analysis based on (Fumi et al., 2013) was followed to model the next 50-year future gold price. Fig. 7 shows the plot of the historical gold prices and the forecast for the next 50-year future gold price. The average inflation rate compounded annually for the past 20 years was estimated as 1.87% (Triami Media, 2016). This value was however not used in the forecasting of the gold price since the historical data is already inflation-adjusted based on the actual year-on-year inflation rates. This ensured the forecast data were more precise and very close to the average trend value. An estimated future gold price of C$ 2,400 (USD$ 1,777) per ounce was used for the evaluation of the proposed framework. This corresponds to future mining in the year 2050; which is the next expected large-scale trend gold mining boom beyond 2017.

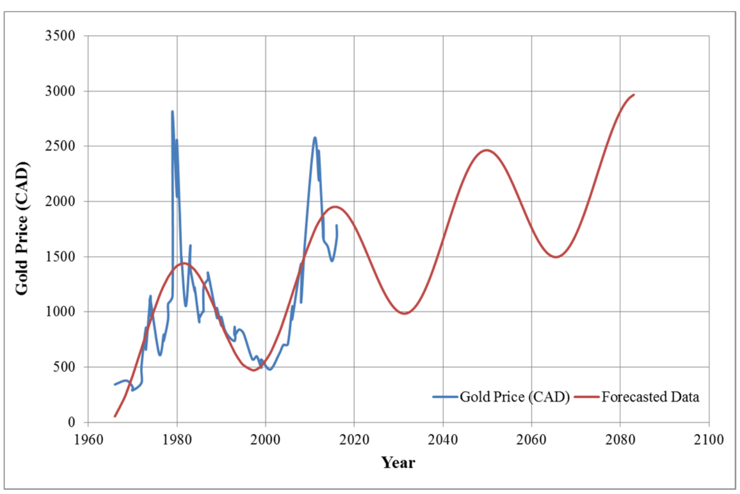

Fig. 7: Historical and forecasted gold price trends

2.4. Processing recovery forecast data

The estimated gold recovery per the feasibility reports of the two open pit gold mines are 93.5% and 92.5%. However, an estimated average gold recovery of 93% was used for the evaluation of the conventional framework. Currently, gold mining companies such as the Tarkwa Mine of Goldfields Ghana Limited and South Deep Gold Mine of Goldfields South African Limited are able to respectively achieve average processing recoveries of 96.5% and 97% (Goldfields, 2016). Based on historical gold recovery performance (Eissler, 1896; Mitchell et al., 1997), and current gold processing recoveries, the future gold processing recovery efficiency used for the proposed framework was forecasted to be 99%.

2.5. Comparative evaluation of the mining and waste management systems

Waste rock management based on the current conventional waste management system and the three scenarios of the proposed waste management options were evaluated using current and future economic, technical and processing parameters as discussed in Section 2. A run-of-mine (RoM) pad with a minimum Au grade of 0.50 g/t was created while a mineralized waste stockpile with a minimum Au grade of 0.01 g/t was also created for the evaluations. A discount rate of 10% was applied during the period when the mine is exploited per the conventional waste management system. After this period, a discount rate of 8% was applied until the remaining orebody was mined out. Applying a discount rate of 8% after the conventional mine life is due to a reduction in the associated risk of the project since more information in relation to the orebody characteristics is well understood. The processing capacity of the plant was 4.2 Mt/year and the mining capacity was 20 Mt/year. For this research, the mining recovery fraction and the mining dilution fraction were each set to 1.0 for the case studies.

3. Results and Discussions

The conventional practice of waste management was evaluated and the results compared to the results from the three scenarios of the proposed framework namely: Scenario 1 - future gold price increase; Scenario 2 - future processing recovery advancement; and Scenario 3 - future increase in gold price and processing recovery advancement. The results are summarized in Table 2.

Fig. 8 shows a comparison of the NPV computed for the conventional practice and the three proposed waste management options. The NPV of Scenarios 1 and 2 were lower than the NPV of the conventional practice. The NPV of the proposed waste management system in Scenario 3 (C$ 427.6 M) increased by 12.6% compared to the NPV of the conventional waste management practice (C$ 379.9 M).

The comparison indicates that, the combined effect of future increase in gold price and technological advancement (processing recovery), Scenario 3, was the option with the best performance. With a total ore resource of 98.7 Mt, Scenario 3 depleted 91.1 Mt of ore, constituting about 92.3% of the entire resource. This indicates that 7.7% of the mineralized material (7.6 Mt) is left unmined. The quantity of mined and processed mineralized material per the conventional waste management practice is 58.8 Mt, constituting about 59.5% of the existing total resource. The current waste management practice which is based on the concept of economic depletion will leave about 40.4% of the mineralized material behind. The proposed waste management framework ensured a mineral resource depletion ratio increase from 59.5% to 92.3%.

The cumulative cashflow for the three proposed scenarios and the conventional practice is shown in Fig. 9. The drop in the cashflow for both Scenarios 1 and 3 at the 17th year indicates the period after the conventional life of mine when lower grades are mined in the extended mine life because of the increased gold price.

The life of mine (LoM), payback period and internal rate of return (IRR) of the mine based on the conventional waste management and the three scenarios of the proposed waste management systems have been compared in Fig. 10. As expected, the payback period and the IRR were better for the conventional practice compared to the proposed waste management framework. The IRR decreased from 14.1 to 13.2% while the payback period increased from 5.4 to 8.9 years. The estimated life of mine per the implementation of the proposed waste management framework (Scenario 3) will increase by 82.7%, from 16.2 to 29.6 years compared to the conventional waste management practice.

Table 2: Summary of results for conventional and proposed waste management systems

Description	Ore Tonnage	Conventional Practice	Future Price Increase	Future Tech Increase	Future Price & Tech Increase
ORE 1 (gold grade ≥ 0.5 g/t) (Mt)	76.2	62.1	71.2	71.2	71.2
ORE 2 (0.01 < gold grade < 0.5 g/t) (Mt)	22.5	3.0	14.5	13.6	19.9
Total Material Mined (Mt)		65.1	85.7	84.8	91.1
Mineralized Material Processed (Mt)		58.8	80.2	78.5	91.1
Mineralized Material Processed (%)		59.5	81.3	79.5	92.3
Unmined and Unprocessed Mineralized Material (Mt)		39.9	18.5	20.2	7.6
Stripping Ratio		2.58	5.46	5.52	5.08
NPV (MC$)		379.9	374.4	249.3	427.6
NPV Compared to Conventional (%)		0.0	-1.4	-34.4	12.6
Life of Mine (Years)		16.2	28.4	28.4	29.6
Payback (Years)		5.4	8.9	8.9	8.9
IRR (%)		14.1	12.9	12.4	13.2

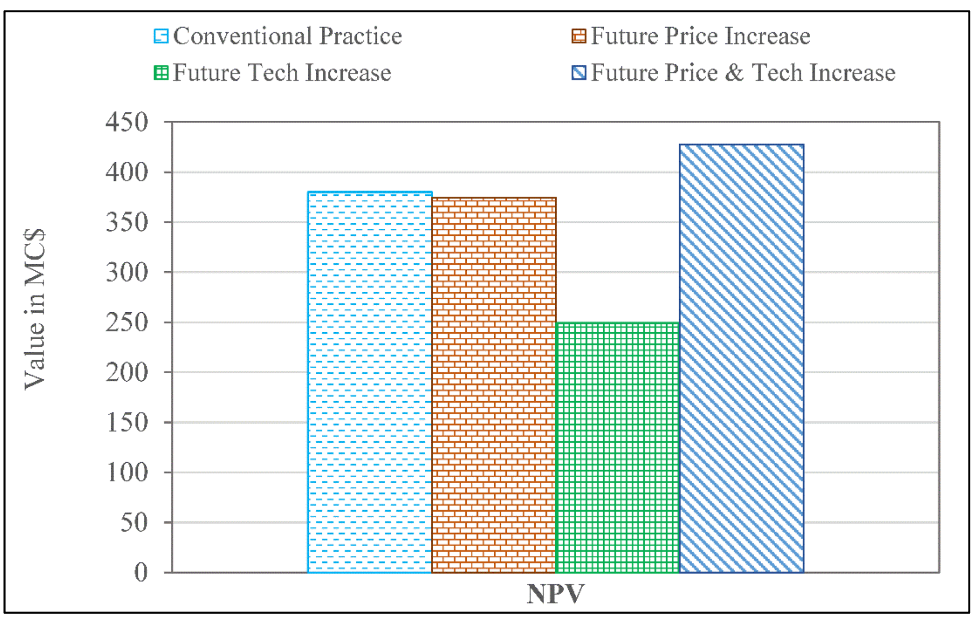

Fig. 8: Comparison of estimated NPV

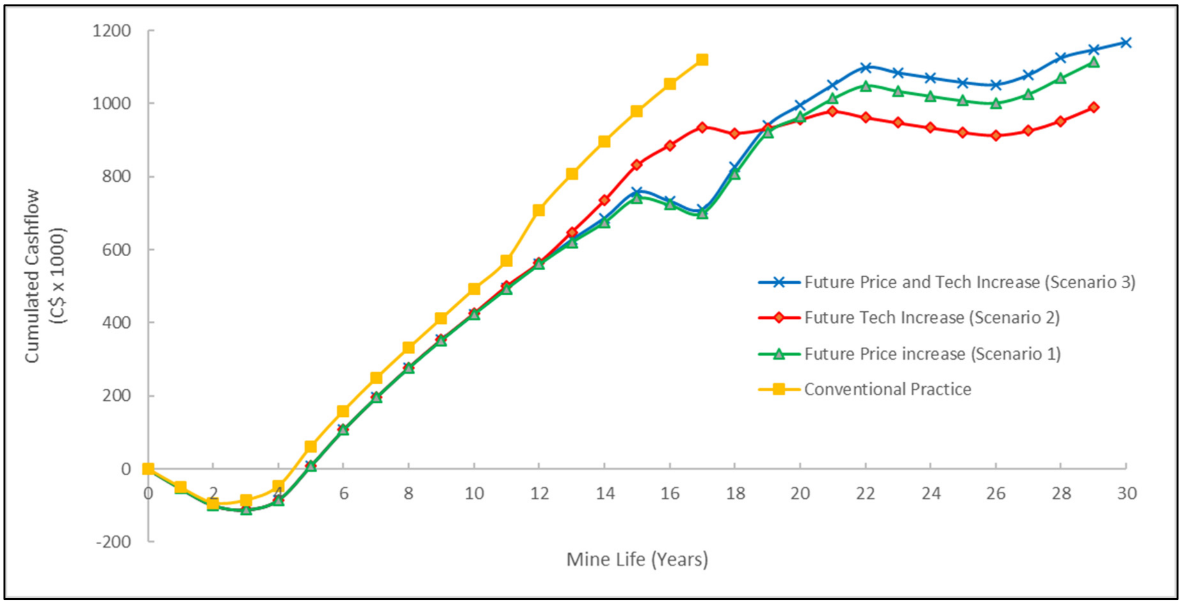

Fig. 9: Comparison of cumulative cashflows

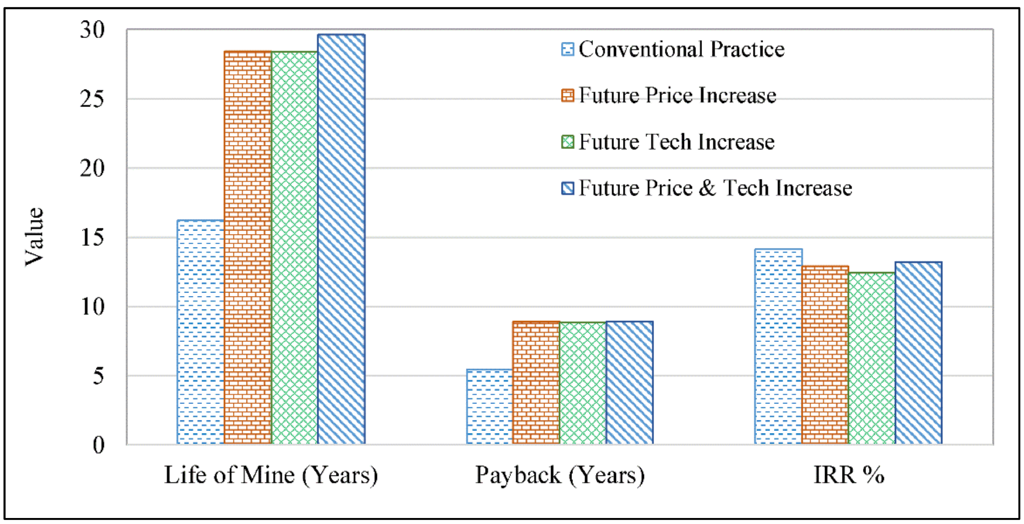

Fig. 10: Comparison of estimated life of mine, payback period and internal rate of return

4. Conclusions

The conventional waste management system does not consider the possibility of mining the mineralized waste during the life of mine. This system abruptly assumes that mining only continues until the ore is economically depleted rather than physical depletion. The potential of the mineralized waste possibly becoming beneficial in the future based on changes in the mineral prices, processing plant recovery or both are not typical considerations of most current strategic mine plans.

The utmost concern is the quantity of mineralized resources that are left unmined in the ground, sent to waste dumps or unprocessed. This reduces the overall mineral resource and the global minerals availability. The conventional waste rock management practice results in mineralized waste materials being extracted from the ground and not evaluated for their potential but rather mixed with non-mineralized waste materials and further left occupying larger surface areas with all its associated environmental challenges. The mineralized waste rock that is completely mixed with the non-mineralized waste rock on the waste dump will lose its asset value since it can no longer be processed.

The proposed waste management framework ensures that, mineral resources are planned towards physical depletion as opposed to the current economic depletion strategy of the mining industry. Evaluation of the proposed framework with the case study indicates 92.3% depletion ratio as opposed to 59.5% depletion ratio per the conventional practice. The additional 13.4 years mine life will enhance sustainability of the mine, employability of workers, positive societal impacts and continual flow of governmental tax benefits. In addition, the proposed framework will further reduce environmental footprints. The future economic benefits of the mine during the implementation of the proposed waste management framework, coupled with several social and economic benefits of the country hosting the mineral deposit is worth exploring.

5. Recommendations

Mining companies should explore the proposed mining and waste management framework presented in this paper during their strategic long-term mine planning. With lessons from Directive 082 (Ellis, 2016), resource rich countries should establish a legislative minimum cut-off grade or an index to determine the minimum cut-off grade of mineral deposits. If the economic cut-off grade is higher than the legislative cut-off grade, then companies must stockpile and document the mineralized resource, and then filed with the government for potential extraction in the future. Furthermore, mining regulations of these countries should be amended to ensure mining companies operate with a legislated minimum processing plant recovery below which they must be investigated.

For extended mine life, governments should consider supporting companies to sustain their mining operations after the economic mine life based on the conventional mining and waste management system. Some of the suggested supports include: 1) tax reliefs or tax reductions; 2) low interest rate government loans; and 3) reduction of fees charged on mining machinery imported.

Future research works are required to evaluate the potential of tailings generated throughout the life of mine as a future mineral resource. Further efforts should also be made to forecast mining cost into the future as new mining systems like autonomous mining and larger more efficient mining equipment have the potential to reduce mining cost as shown by historical trends.

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Incorporating Stockpiling and Cut-off Grade Optimization into Oil Sands Production and Dyke Material Planning using Goal Programming

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ABSTRACT

In achieving maximum benefit in oil sands mining, the time and sequence of removing ore, dyke material and waste from the final pit limit is essential to the long-term production schedule. In-pit waste management strategy requires the simultaneous construction of dykes with the advancement of mining operations. This paper seeks to determine: 1) the time and sequence for removal of ore, dyke material and waste to maximize Net Present Value (NPV); 2) the quantity of dyke material required for dyke construction to minimize construction costs; and 3) the impacts of stockpiling and stockpile reclamation with limited time duration. An Integrated Cut-Off Grade Optimization (ICOGO) model was used to generate an optimum cut-off grade policy and a schedule for mining ore and waste, as well as overburden, interburden and tailings coarse sand dyke materials in long-term production planning. Subsequently, a Mixed Integer Linear Goal Programming (MILGP) model was developed to generate a detailed production schedule for removal of ore, waste and dyke materials from the final pit limit. The cut-off grade profile and schedule generated by the ICOGO model are used as guides to define the grade constraints and production goals required by the MILGP model. The developed models feature stockpiling with limited duration for long-term production scheduling. The models were applied to an oil sands case study to maximize the NPV of the operation. In comparison, whereas the ICOGO model solved the optimization problem faster, the MILGP model results provided detailed mining-cut extraction sequencing for practical mining.

1. Introduction

Effective waste management drives the sustainability and profitability of oil sands mining operations. Currently, more than 80% of the processed oil sands ore are deposited in tailings dams, which are constructed at designated areas outside the final pit limit, or in mined out areas of the active pit (Masliyah, 2010). Generating such large volumes of tailings material during mining has caused several environmental issues. To reduce the environmental footprints for oil sands mining, the regulatory requirements of the Alberta Energy Regulator (AER) Directive 085 require oil sands mining companies to integrate waste management strategies into their long-term production plans (Ellis, 2016b). For this reason, simultaneous in-pit dyke construction and tailings deposition has been introduced as the mine advances; in a way that when a pushback is available, a dyke is constructed to generate a tailings containment area. The material required for dyke construction primarily comes from the mining operation, which includes overburden (OB), interburden (IB) and tailings coarse sand (TCS) dyke material. These materials must meet the fines requirements for

This paper was submitted to the Computers and Operations Research Special Issue in Mine Planning in August, 2017

dyke construction. Material that cannot be classified as ore or dyke material are considered to be waste material (Ben-Awuah and Askari-Nasab, 2011; Ben-Awuah et al., 2012).

Heuristic algorithms and exact solution methods are the two main research areas in optimizing the production scheduling process (Askari-Nasab and Awuah-Offei, 2009). Lane (1964) developed a comprehensive heuristic optimization model to determine the optimum cut-off grade policy and generate the life of mine production schedule in terms of material tonnages. The model does not take into consideration waste management cost as required for integrated oil sands mine and waste disposal planning. This lead to the development of a modified version of Lane's model referred to in this research as the Integrated Cut-Off Grade Optimization (ICOGO) model. The ICOGO model allows for determining the optimum cut-off grade policy in the presence of waste management for dyke construction and stockpiling with limited duration. The developed model considers stockpile re-handling and waste management costs, and generates production schedules for multiple material types. The ICOGO model is fast to implement but does not take into account detailed mining-cut extraction sequencing during optimization.

Subsequently, a theoretical mathematical programming framework based on Mixed Integer Linear Goal Programming (MILGP) model was developed to generate detailed long-term production plans for integrated oil sands mining and waste management. The MILGP model maximizes the NPV and minimizes dyke construction cost, as well as implements stockpiling with limited duration for oil sands mining. Solving long-term production scheduling problems using mathematical programming models with exact solution methods is a preferred approach considering that the extent of optimality of the solution is known. However, mathematical programming frameworks are computationally expensive and this increases exponentially with the problem size (Ben-Awuah and Askari-Nasab, 2011). Heuristic methods are usually computationally cheaper since they follow an iterative process to generate the best results among alternate options, though the optimality of the solution cannot be guaranteed. The cut-off grade profile and schedule generated by the ICOGO model are used as a guide to define the grade constraints and production goals required by the MILGP model. This technique is synonymous to providing a customized initial solution to the MILGP model, thereby decreasing the size of the solution space and facilitating a reduced solution time for the MILGP framework.

The next section of this paper presents a discussion on the problem definition. Section 3 reviews relevant literature related to cut-off grade optimization and open pit production planning algorithms. Section 4 highlights development of the theoretical frameworks for ICOGO and MILGP models and Section 5 discusses the application of the ICOGO and MILGP models with an oil sands case study. The paper concludes in Section 6.

2. Problem definition

Taking waste management into consideration during long-term production scheduling poses challenges related to creating an optimized mining schedule. The integration of the production schedule and waste management strategy increases the size of the optimization problem significantly. Incorporating various material types, elements, and destinations as well as providing an available in-pit area for construction of dykes are a few of the parameters that need to be taken into consideration resulting in a large-scale optimization problem.

An agglomerative hierarchical clustering algorithm developed by Tabesh and Askari-Nasab (2011) is used to create mining-cuts. Blocks within the same level are grouped together based on their attributes such as location, rock type and grade to build up a mining-cut. The intersection of a group of mining-cuts belonging to the same mining bench and a mining-phase (pushback) is referred to as a mining-panel. Each mining-cut within a mining-panel contains: 1) ore material, 2) TCS dyke material (from processed ore), 3) OB and IB dyke material and 4) waste. Figure 1 illustrates the material flow for an oil sands mine containing K mining-cuts and M pushbacks.

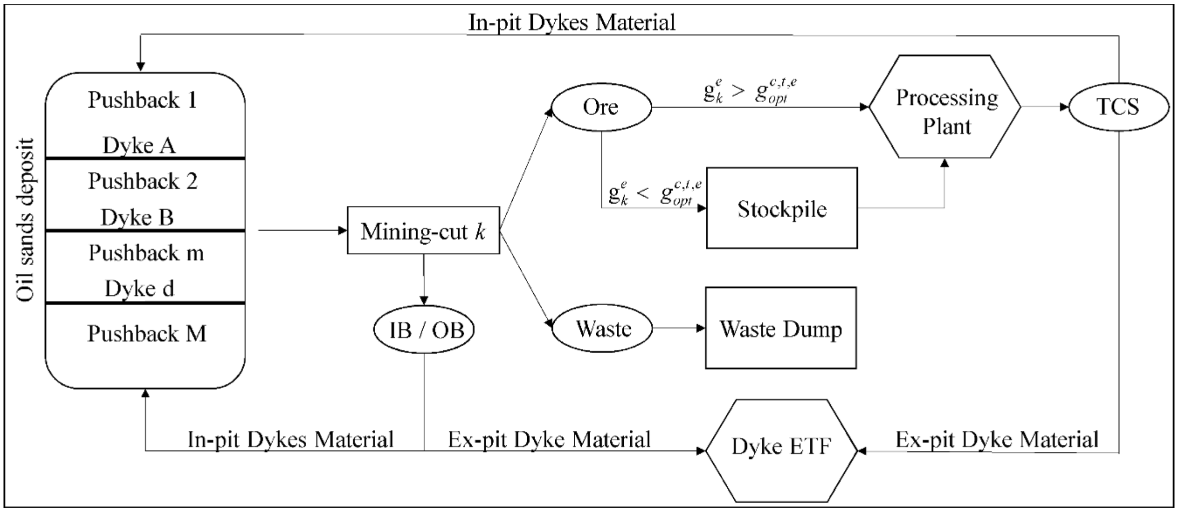

Figure 1: Material flow for oil sands production planning and waste management modified after Ben-Awuah et al. (2012)

Using Ben-Awuah et al. (2012) model as the starting point, this paper focuses on developing an MILGP model to generate a detailed production schedule for different material types and destinations. The Ben-Awuah et al. (2012) model does not provide information on how initial grade boundaries and production targets were defined and they do not consider stockpiling in their model development.

First, a heuristic cut-off grade optimization model was developed considering waste management cost for ex-pit and in-pit dyke construction, and stockpiling with limited duration. The main objective is to develop and implement an Integrated Cut-Off Grade Optimization (ICOGO) model to generate an optimum life of mine cut-off grade profile and production schedule for different material types. The ICOGO model development starts with Lane's (1964) model and includes waste management cost and stockpiling with limited duration as required in oil sands mining.

Subsequently, an MILGP model was developed to use the cut-off grade profile and schedule generated by the ICOGO model as a guide to define the grade constraints and production goals required by the MILGP model. By this approach, the optimization solution space will be limited and the optimum solution found faster. The developed MILGP model features stockpiling with limited duration for long-term production scheduling.

The main objectives of the paper can be classified into four focus areas:

1. Maximize the NPV and minimize dyke construction cost of the operation by determining the time and sequence for removal of ore, dyke material and waste from the final pit limit;
2. Minimize deviations from production goals (grade and tonnage) which are outcomes from the ICOGO model;
3. Evaluate the impact of stockpiling and stockpile with limited duration in oil sands mining;
4. Investigate the impact of the two-step approach on the solution time.

3. Summary of literature review

In 1964, Lane developed a cut-off grade optimization model based on economic factors, grade-tonnage distribution, and operational capacities. The objective function of Lane's model is to maximize the NPV of the operation with respect to capacities of the mining, processing and refinery processes. He considered the concept of opportunity costs in his model to generate a dynamic cut-off grade policy for the life of mine (Lane, 1964). The dynamic nature of Lane's model requires the use of stockpiling. The material between the optimum grade and the lowest cut-off grade can be stockpiled during the mining operation for possible future reclamation (Asad et al., 2016). Lane's model needs the general extraction sequence as an input to the optimization process and generates the production schedule in terms of material tonnages and grades. An extension of Lane's original theory for deposits containing two economic materials was developed by Asad (2005) to incorporate stockpiling into the production scheduling problem. The stockpile acts as an additional pushback when active pit mining is completed. He noted that problems such as leaching, deterioration of material and oxidation, can happen due to long-term stockpile duration. He also demonstrated with a hypothetical case study that his model could increase the NPV of the mining operation.

During the past four decades, many researchers have developed extensions to Lane's model for deposits with single and multiple economic minerals. In order to find the optimum cut-off grade policy and production schedule, Osanloo and Ataei (2003) presented a golden section search method with equivalent grade factor for Lane's model. Genetic algorithm, golden section search, equivalent grade method and iterative grid search have been used by Ataei and Osanloo (2003a; 2003b; 2004) to generate the optimum cut-off grade policy and production plan in complex ore deposits. An application of the grid search technique for deposits with more than two economic minerals was also investigated by Cetin and Dowd (2013).

The problem of open pit production scheduling can be described as specifying the sequence in which mining blocks should be removed to maximize the NPV of the deposit, with respect to physical and economic constraints. The main constraint for production scheduling is the block extraction sequencing (Whittle, 1989). Some optimization frameworks for mine production planning such as Lane's model define production levels in terms of tonnage and grade. This concept can reduce complex computations; however, it ignores the detailed block extraction sequencing, which is the most important part of mine production planning (Gershon, 1983).

Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) models are some of the most robust techniques used for solving mine production scheduling problems since the 1960s. These models can consider thousands of decision variables and constraints. LP and MILP problems are solved using exact optimization methods which provide a single solution within the set optimality tolerance. The LP and MILP models are generated as a system of equations which makes them easy to use for multiple projects, requiring only minor changes to be made to them. On the other hand, like other Mathematical Programming Models (MPMs), LP and MILP models are computationally costly, which can be difficult to handle for large problems with thousands of variables and equations (Huttagosol and Cameron, 1992).

Manula (1965), Johnson (1969) and Meyer (1969) were among the firsts to initiate development of LP and MILP models in mine planning optimization. One of the main obstacles that these authors encountered was solving large integer programming problems. Despite the models' remarkable success, LP and MILP have not become the preferred method for mine planning due to computational difficulties (Gershon, 1983). One of the most critical aspects of the production scheduling process is to determine a feasible mining sequence. Therefore, it is vital to follow the block extraction precedence relationships in the optimization process to ensure the long-term plan is practically feasible (Gershon, 1983).

During the past three decades, many authors have made efforts to overcome the problem of solving large scale optimization problems in a timely manner. The lagrangian relaxation algorithm is one of the methods that was adopted by Dagdelen (1985) and Dagdelen and Johnson (1986). Another method is the branch-and-cut algorithm which was used by Caccetta and Hill (2003) to solve large scale optimization problems. Binary variables are the main reason which makes solving the optimization problem difficult. One technique for solving the large-scale problem is to reduce the size of the problem prior to optimization. Ramazan and Dimitrakopoulos (2004) reduced the number of binary variables to solve the optimization problem faster. In order to reduce the number of binary variables even more, Ramazan et al. (2005) and Ramazan (2007) used an aggregation method and solved the problem with a fundamental tree algorithm. However, using their method may eliminate the global optimum solution due to the method of reduction of the problem size. Askari-Nasab et al. (2010) applied MILP formulations to an open pit iron ore mine production schedule and compared their results to an industry strategic mine planning software, Whittle (GEOVIA Whittle, 2013). In order to reduce the size of the optimization problem, they aggregated the mining blocks into mining-cuts using a clustering algorithm and claimed that the generated NPV of the MILP model was 2.6% higher than the NPV generated by Whittle Milawa Balanced algorithm (GEOVIA Whittle, 2013). They conclude that MILP formulations based on processing and extraction at mining-cut level, are models that maximize NPV and suitable for long-term planning with efficient computation time.

Another MPM used for Long-Term Production Planning (LTPP) problems is Goal Programming (GP). The benefit of using GP over other mathematical programming models is being able to prioritize one goal over another. Zhang et al. (1993) used GP for LTPP of a mining operation with a single ore type process. They verified their model by applying it to an open pit coal mine. Chanda and Dagdelen (1995) and Esfandiari et al. (2004) also applied GP to the LTPP problem; however, they mentioned that the application of GP is impractical due to the size of the problem and large number of constraints. Research shows that there is a greater advantage using MILP and GP together. Industries such as manufacturing and operations management are taking advantage of the application of MILGP models (Selen and Hott, 1986; Liang and Lawrence, 2007; Sen and Nandi, 2012).

Ben-Awuah and Askari-Nasab (2011) formulated, implemented and tested a theoretical MILGP framework for oil sands production scheduling and waste management. Their model could handle multiple material types and elements in LTPP, and maximize the NPV of the operation. Ben-Awuah et al. (2012) completed their work by considering multiple destinations for dyke material, including in-pit and external tailings facilities for waste management. They used MILGP because the formulation structure allows the optimizer to achieve a set of goals, whilst some goals can be traded-off against others based on their priority. In addition, hard constraints that could result in infeasible solutions can be changed to soft constraints. Implementation of their model resulted in maximum NPV while creating timely tailings storage areas. It should be mentioned that the main limitation with their model is the absence of stockpile management and long runtime (Ben-Awuah et al., 2012). In order to reduce the solution running time, Ben-Awuah and Askari-Nasab (2013) used a pre-processing approach to reduce the number of non-zero and integer decision variables. Results from their case studies showed a reduction in the solution time by more than 99% (Ben-Awuah and Askari-Nasab, 2013).

Over the past decades, researchers have improved the cut-off grade optimization framework introduced by Lane in 1964 by incorporating different parameters into the cut-off grade calculation. This research seeks to incorporate waste management cost and stockpiling simultaneously into an integrated cut-off grade optimization model for oil sands mining. Furthermore, the research explores the incorporation of a limited duration stockpiling strategy in a two-step mathematical programming framework for integrated mine planning and waste management as required in oil sands mining. The practical implementation of the cut-off grade optimization and mathematical programming models are discussed.

4. Theoretical framework

4.1. Block Modelling

For scheduling optimization of an open pit mine, the orebody is discretized as a block model comprising of three-dimensional arrays of cubical blocks. The number of blocks in the block model is related to the size of the deposit. The geology of the deposit and the preferred size of mining equipment can be used to identify the dimensions of the blocks in the block model. Characteristics of the blocks including rock type, density, grade and economic data can be expressed numerically (Askari-Nasab et al., 2011). The blocks in the block model consist of smaller units called parcels, which contain information on rock-type, tonnage and element content. The ore tonnage and the block grade can be used to estimate the quantity of minerals in a block. The spatial location of each block within the block model is determined by the coordinates of its center. However, the shape and location of the parcels within each block are not specified (Askari-Nasab and Awuah-Offei, 2009). The ultimate pit limit (UPL) can be generated using the block model as input to Whittle strategic mine planning software (GEOVIA Whittle, 2013) which is developed based on the Lerchs and Grossmann (LG) algorithm (Lerchs and Grossmann, 1965).

4.2. Break-Even Cut-Off Grade Optimization

Cut-off grade optimization was used to maximize the NPV of oil sands mining operations with respect to limited processing capacity. The ICOGO model incorporates dyke construction costs into cut-off grade optimization and generates the optimum cut-off grade profile and production schedule for ore, dyke material, and waste. The results from the ICOGO model were used as a guide to define grade boundaries and production targets in the MILGP model.

The oil sands ore has grade dependent recovery factor. According to Directive 082 (Ellis, 2016a), the processing recovery factor for oil sands ore can be calculated based on average weight percent bitumen content of the as-mined ore. Figure 2 shows the profile for oil sands ore processing recovery factor.

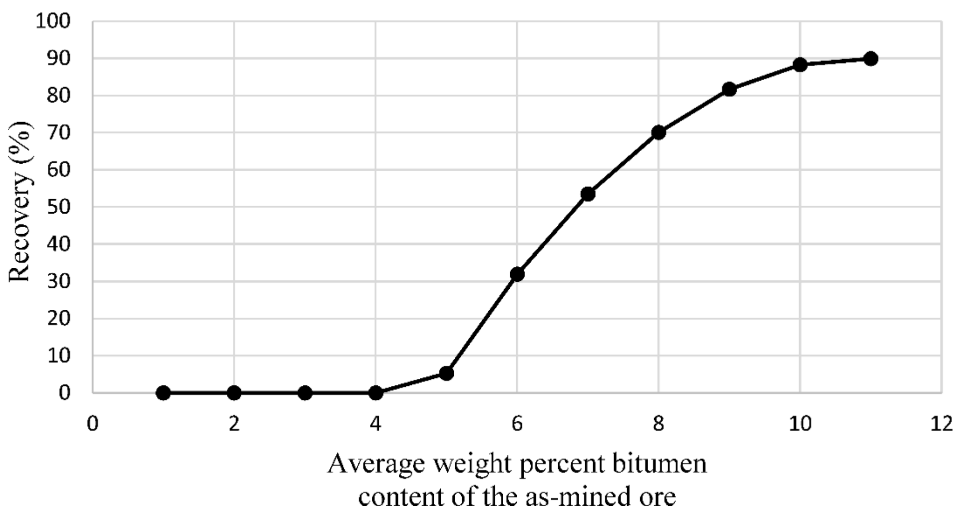

Figure 2: Profile for oil sands ore processing recovery factor

Based on the grade-recovery relationship, the break-even cut-off grade for oil sands mining was determined with Whittle (GEOVIA Whittle, 2013). In this paper, the break-even cut-off grade is referred to by the term 'lowest acceptable grade'. Whittle generated a lowest acceptable grade of 6% for the oil sands ore. From Figure 2, material with bitumen grade less than 6% have less than 31% recovery and are therefore not economical to process. During stockpiling, the ore material oxidizes and the processing recovery begins to deteriorate. For the purpose of this research, it was assumed that the processing recovery deteriorates by 1% for each year stockpiled. In addition during the cut-off grade optimization calculation, a weighted average recovery factor was used which is more representative of the mineralization.

4.3. The Integrated Cut-Off Grade Optimization (ICOGO) Model

Considering the lowest acceptable bitumen cut-off grade of 6%, the material in the final pit limit was classified as ore, dyke material, and waste. Extending Lane's (1964) model, the ratio of the amount of dyke material should be related to the total amount of ore and waste to allow the incorporation of dyke construction costs into the cut-off grade optimization process. Equation (1) shows the ratio of the TCS dyke material to the total amount of ore, and Equations (2) and (3) show the ratio of OB and IB dyke material to the total amount of waste, respectively. The variables used in developing the equations have been defined in the Appendix.

$$R_{TCS} = \frac{Total\ amount\ of\ TCS\ dyke\ material}{Total\ amount\ of\ ore} \tag{1}$$

$$R_{OB} = \frac{Total\ amount\ of\ OB\ dyke\ material}{Total\ amount\ of\ waste} \tag{2}$$

$$R_{IB} = \frac{Total\ amount\ of\ IB\ dyke\ material}{Total\ amount\ of\ waste} \tag{3}$$

Using the calculated ratios for dyke material, the profit expression for oil sands mining and waste management operations can be determined by Equation (4). The mine life and the amount of product can be calculated by Equations (5) and (6) respectively, for a processing limited mining operation.

If the maximum processing rate is the limiting operational constraint, to calculate the optimum cut-off grade, Equations (5) and (6) should be substituted in Equation (4) to get Equation (7). Taking the derivative of Equation (7) with respect to grade and setting it to zero will result in the optimum cut-off grade. In Equation (8), the amount of material to be mined is independent of the grade; which makes *dqm/dg = 0*. Therefore, to make Equation (8) equal to zero, Equation (9) which is the first part of Equation (8) should be equal to zero. Solving Equation (9) for grade generates the optimum cut-off grade (Equation (10)). Details of an iterative algorithm used in generating the optimum cut-off grade profile and production schedule for oil sands mining considering waste management for dyke construction, and stockpiling with limited duration for a processing limited operation is presented in Seyed Hosseini (2017). Figure 3 illustrates the flow diagram of the iterative algorithm for implementing the ICOGO model.

Profit = Revenue - Processing Cost - Mining Cost - TCS Cost - OB Cost - IB Cost - Annual Fixed Cost

$$pr = (sp - sc)qr - pc.qp - mc.qm - tc.R_{TCS}.qp - bc.R_{OB}.(qm - qp) - ic.R_{IB}.(qm - qp) - FT \tag{4}$$

$$T_p = \frac{qp}{QP} \tag{5}$$

$$qr = g_{avg}.r_{avg}.qp \tag{6}$$

$$pr = \left((sp - sc).g_{avg}.r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP} \right).qp - \left(mc + bc.R_{OB} + ic.R_{IB} \right).qm \tag{7}$$

$$\frac{dpr}{dg}=\left(\left(sp-sc\right).g_{avg}.r_{avg}-pc-tc.R_{TCS}+bc.R_{OB}+ic.R_{IB}-\frac{F}{QP}\right).\frac{dqp}{dg}-\left(mc+bc.R_{OB}+ic.R_{IB}\right).\frac{dqm}{dg}=0 \quad (8)$$

$$\left(\left(sp-sc\right).g_{avg}.r_{avg}-pc-tc.R_{TCS}+bc.R_{OB}+ic.R_{IB}-\frac{F}{QP}\right)=0 \quad (9)$$

$$g_p=\frac{pc+tc.R_{TCS}-bc.R_{OB}-ic.R_{IB}+\dfrac{F}{QP}}{\left(sp-sc\right).r_{avg}} \quad (10)$$

.

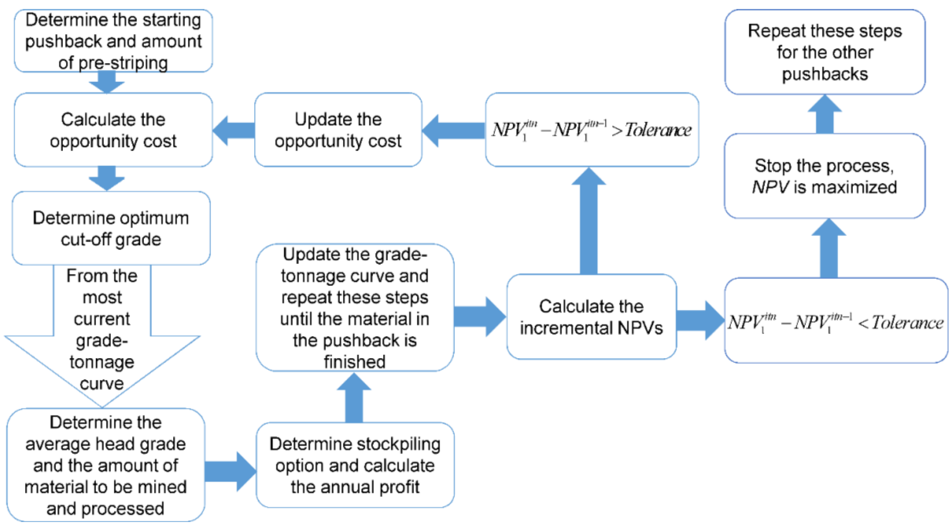

Figure 3: Flow diagram of iterative algorithm for implementing ICOGO model (Seyed Hosseini, 2017)

4.4. The Mixed Integer Linear Goal Programming (MILGP) Model

4.4.1. Block Clustering

A substantial challenge in finding the long-term optimal production schedule is a lack of adequate computer memory space during optimization calculations due to the exponential growth of the problem size with an increase in the number of blocks. The integer decision variables used in constructing the block mining precedence constraints require large computational resources during optimization. Employing clustering and paneling approaches reduce the optimization problem size and ensure minimum mining width is practical for the large mining equipment used in oil sands mining.

In this research, an agglomerative hierarchical clustering algorithm developed by Tabesh and Askari-Nasab (2011) is used in aggregating mining blocks into mining-cuts for solving the mine production scheduling problem. The clustering algorithm is customized for mine production planning problems. Using this algorithm, ore data is summarized as well as the total quantity of elements contained in the mining-cuts from the mining blocks. Also, the separation of lithology is maintained. Mining-cuts are made up of blocks within the same level and are grouped based on their attributes; location, rock type, and grade. Mining-panels are made up of mining-cuts and are used to control the mine extraction sequence. A mining-panel is the intersection of the material in a mining phase/pushback and a mining bench (Ben-Awuah and Askari-Nasab, 2013). Figure 4 shows the relation between blocks, mining-cuts and mining-panels on a level.

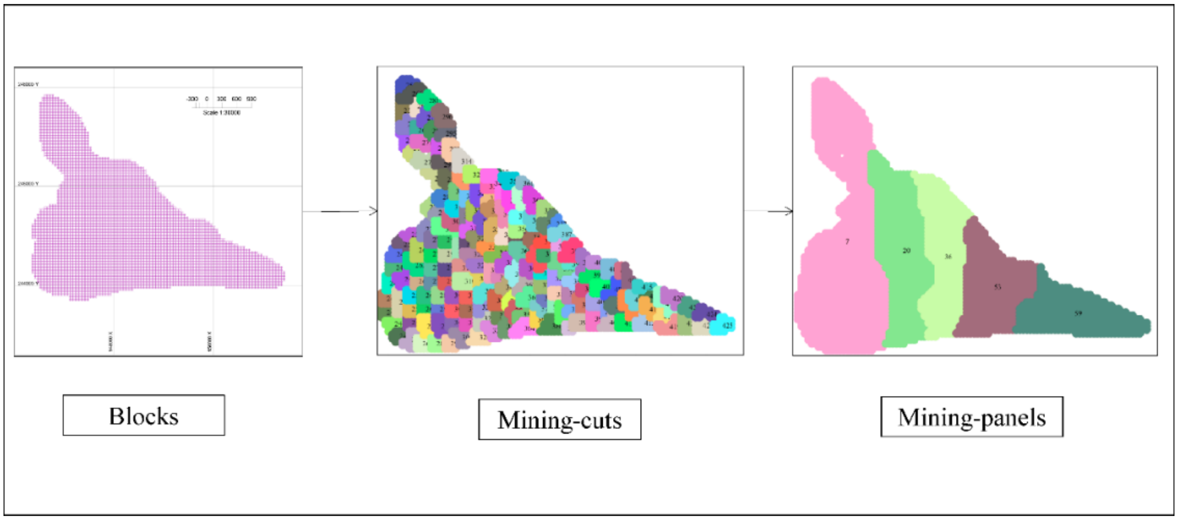

Figure 4: Relation between blocks, mining-cuts and mining-panels on a level

4.4.2. Economic Mining-cut Value

Each mining-cut has an economic value based on mining blocks which can be mined selectively within the mining-cut. The total discounted cost involved in excavating each mining-cut are: the base discounted mining costs for excavating mining-cut K as waste; the extra discounted costs of processing the ore parcels contained in the mining-cut K at the designated processing destination; the extra discounted costs of excavating OB, IB and the generated TCS dyke material from mining-cut K for dyke construction at a designated destination; and the discounted annual fixed cost. The discounted profit generated from extracting each mining-cut can be defined based on the total discounted revenue generated from selling the final product within each mining-cut minus the total discounted cost involved in extracting the mining-cut. Mining-panels are made up of mining-cuts that belong to the same pushback and mining bench. The sum of the discounted economic mining-cuts values within each mining-panel determines the discounted economic mining-panel value.

Equation (11) shows the discounted economic mining-cut value for mining-cut K that is sent from the mine to the plant. Equation (12) shows the discounted economic mining-cut value for mining-cut K that is sent from the stockpile to the plant.

$$d_k^{d,t} = v_k^{c,t} - c_k^{l,t} - eo_k^{d,t} - ei_k^{d,t} - et_k^{d,t} \tag{11}$$

$$d_{k,s}^{d,t} = sv_{k,s}^{c,t} - c_k^{l,t} - eo_k^{d,t} - ei_k^{d,t} - et_k^{d,t} \tag{12}$$

Equations (13) to (18) define the parameters in Equations (11) and (12). Equation (13) defines the discounted revenue generated from selling the final product within each mining-cut K minus the discounted cost of processing, minus the discounted annual fixed cost. Equation (14) defines the discounted revenue generated from selling the final product within each mining-cut K processed from the stockpile, minus the discounted cost of processing, minus the extra discounted cost of re-handling the stockpile material, minus the discounted annual fixed cost. Equation (15) defines the base discounted mining cost for extracting mining-cut K as waste. Equations (16) to (18) show the extra discounted cost of mining OB, IB and TCS dyke material respectively, from mining-cut K to the appropriate dyke construction destinations.

$$v_k^{c,t} = o_k g_k^e r_{avg}^{c,e} (sp^{e,t} - sc^{e,t}) - o_k pc^{c,e,t} - o_k \left(\frac{F^t}{PT^{c,t}} \right) \tag{13}$$

$$sv_{k,s}^{c,t} = o_k g_k^e r_{avg,s}^{c,e} (sp^{e,t} - sc^{e,t}) - o_k pc^{c,e,t} - o_k kc_s^{c,e,t} - o_k \left(\frac{F^t}{PT^{c,t}} \right) \tag{14}$$

$$c_k^{l,t} = (o_k + od_k + id_k + w_k) mc^{l,t} \tag{15}$$

$$eo_k^{d,t} = od_k bc^{d,t} \tag{16}$$

$$ei_k^{d,t} = id_k ic^{d,t} \tag{17}$$

$$et_k^{d,t} = td_k tc^{d,t} \tag{18}$$

Using these equations, the economic mining-cut value of material from mine to plant or from stockpile to plant can be evaluated.

4.4.3. MILGP Objective Function

In order to maximize the NPV of the mine operation, the MILGP model objective function should contain all of the following parameters: determining the time and sequence for removal of ore, dyke and waste material from the UPL; minimizing the dyke construction cost; and minimizing deviations from production goals which are inputs from the ICOGO model. Here, the model presented by Ben-Awuah et al. (2012) was used as a starting point. The MILGP model uses two sets of decision variables: binary integer decision variables to control precedence relation of mining-panels extraction; and continuous decision variables to control the mining, processing, stockpiling, OB, IB and TCS dyke material production requirements. In addition, continuous deviational variables have been defined to control the mining, processing, OB, IB and TCS dyke material production goals, and processing plant head grade goals. These variables provide an option for the user to set a continuous range of units for the optimization process to achieve the targeted goals with acceptable deviations. To prioritize goals and set precedence for achieving one goal over another, priority parameters were defined. The main goal that the user wants to achieve can have the highest priority parameter, ensuring that the optimization process will achieve that goal. For any deviation from the targeted goals, a penalty cost that reduces the NPV can be charged. Prioritized penalty parameters were defined to control deviations from the targeted goals as shown in Equation (21).

Based on the regulatory requirements (Ellis, 2016a), oil sands mining companies cannot leave behind any ore material containing more than 7% bitumen. Based on the initial cut-off grade analysis conducted with Whittle (GEOVIA Whittle, 2013), materials containing more than 6% bitumen have economic potential. During production, it is assumed that all material sent to the stockpile will be reclaimed for processing after a specified stockpiling duration (kd). Stockpiling oil sands ore for longer periods results in oxidation that causes challenges during the bitumen extraction process. To add stockpiling to the MILGP model, a new set of decision variable, $x_{k,s}^{c,t}$, was introduced. Tabesh et al. (2015) modeled a stockpiling decision variable in an MILP model. In their model, stockpiling bins with known grade ranges for each period are considered to avoid a non-linear problem when adding stockpiling to the production scheduling problem. In the MILGP model developed in this research, it was assumed that for every period there are stockpile bins available where material can be sent, and after the stockpiling duration, this material can be reclaimed in entirety with known grades.

The maximization of NPV and minimization of dyke construction costs are determined using Equations (19) and (20). In these equations, continuous decision variables

$y_p^{l,t}$, $x_k^{c,t}$, $x_{k,s}^{c,t}$, $u_k^{d,t}$, $n_k^{d,t}$ and $z_k^{d,t}$ are controlling the mining, processing, stockpiling, OB, IB and TCS dyke material production, respectively. Equation (21) shows the minimization of the deviation variables from the set targets. For mining, processing, OB, IB and TCS dyke material production goals, we define negative deviational variables which are $gd_1^{-,l,t}$, $gd_2^{-,c,t}$, $gd_3^{-,d,t}$, $gd_4^{-,d,t}$ and $gd_5^{-,d,t}$, respectively. However, for average processing plant head grade goal we define negative $\left(gd_6^{-,c,t}\right)$ and positive $\left(gd_6^{+,c,t}\right)$ deviational variables.

$$Max\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{s=1}^{S}\sum_{c=1}^{C}\sum_{t=1}^{T}\left(\sum_{\substack{k\in C_p\\ p\in C_m}}\left(v_k^{c,t}x_k^{c,t}+sv_{k,s}^{c,t}x_{k,s}^{c,t-kd}-c_p^{l,t}y_p^{l,t}\right)\right) \tag{19}$$

$$Min\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{t=1}^{T}\left(\sum_{\substack{k\in C_p\\ p\in C_m}}\left(eo_k^{d,t}u_k^{d,t}+ei_k^{d,t}n_k^{d,t}+et_k^{d,t}z_k^{d,t}\right)\right) \tag{20}$$

$$Min\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{t=1}^{T}\left[\sum_{\substack{k\in C_p\\ p\in C_m}}\begin{pmatrix}PP_1gd_1^{-,l,t}+PP_2gd_2^{-,c,t}+PP_3gd_3^{-,d,t}+PP_4gd_4^{-,d,t}+PP_5gd_5^{-,d,t}\\ +PP_6gd_6^{-,c,t}+PP_7gd_6^{+,c,t}\end{pmatrix}\right] \tag{21}$$

To formulate a single objective function for the MILGP model, Equations (19) to (21) are combined to generate Equation (22).

$$Max\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{s=1}^{S}\sum_{c=1}^{C}\sum_{t=1}^{T}\left[\sum_{\substack{k\in C_p\\ p\in C_m}}\left[\begin{array}{l}\left(v_k^{c,t}x_k^{c,t}+sv_{k,s}^{c,t}x_{k,s}^{c,t-kd}-c_p^{l,t}y_p^{l,t}\right)-\left(eo_k^{d,t}u_k^{d,t}+ei_k^{d,t}n_k^{d,t}+et_k^{d,t}z_k^{d,t}\right)-\\ \begin{pmatrix}PP_1gd_1^{-,l,t}+PP_2gd_2^{-,c,t}+PP_3gd_3^{-,d,t}+PP_4gd_4^{-,d,t}+PP_5gd_5^{-,d,t}+\\ PP_6gd_6^{-,c,t}+PP_7gd_7^{+,c,t}\end{pmatrix}\end{array}\right]\right] \tag{22}$$

4.4.4. MILGP Goal Functions

The MILGP model uses goal functions to accomplish the long-term production targets generated by the ICOGO model. The goal functions for production targets in tonnages are defined by Equations (23) to (27) for mining, processing, OB, IB and TCS dyke material. The average head grade goal function, Equation (28), is defined in terms of grade unit (%mass).

$$\sum_{m=1}^{M}\left(\sum_{p\in C_m}\left(o_p+od_p+id_p+w_p\right)y_p^{l,t}\right)+gd_1^{-,l,t}=MT^{l,t} \tag{23}$$

$$\left[\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p\\ p\in C_m}}\left(o_kx_k^{c,t}\right)\right)+\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p\\ p\in C_m}}\left(o_kx_{k,s}^{c,t-kd}\right)\right)\right]+gd_2^{-,c,t}=PT^{c,t} \tag{24}$$

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p\\ p\in C_m}}\left(od_ku_k^{d,t}\right)\right)+gd_3^{-,d,t}=OT^{d,t} \tag{25}$$

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}}\left(id_k n_k^{d,t}\right)\right)+gd_4^{-,d,t}=IT^{d,t} \tag{26}$$

$$\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}}\left(td_k z_k^{d,t}\right)\right)+gd_5^{-,d,t}=TT^{d,t} \tag{27}$$

$$\frac{\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k g_k^e x_k^{c,t}\right)+\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k g_k^e x_{k,s}^{c,t-kd}\right)}{\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k x_k^{c,t}\right)+\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k x_{k,s}^{c,t-kd}\right)}+gd_6^{-,c,t}-gd_7^{+,c,t}=HT^{c,t} \tag{28}$$

Equation (23) controls the total quantity of material to be mined in each period and $gd_1^{-,l,t}$ allows the acceptable deviation from the mining target defined by the user. Equation (24) determines the total quantity of ore sent to the processing destination in each period from the mine and the stockpile. The quantity of material that was sent to the stockpile in period *t-kd,* is equal to the quantity of material sent to the processing destination from the stockpile in period *t*. In this equation, $gd_2^{-,c,t}$ controls the acceptable deviation from the set processing target. Equations (25) to (27) are the dyke material goal functions. Using these equations, the dyke material production target was set for different dyke construction destinations, which provides a practical schedule for dyke construction. Equation (28) controls the average head grade of the material being sent to the processing destination from the mine and stockpile. The acceptable negative and positive deviations from the set targets are controlled by $gd_6^{-,c,t}$ and $gd_6^{+,c,t}$, respectively. Equation (28) has a non-linear format. The numerator of the first part of the equation is equal to the quantity of element content in each production period and the denominator is equal to the quantity of material processed in each period. Dividing these two, will generate the grade of the material processed. In order to convert Equation (28) to a linear format, the head grade target and deviational variables are multiplied by the processing target to generate element content target. This requires that the set periodic processing targets must be achieved to ensure Equation (28) accurately monitors the head grade in each period.

In general, these goals are defined with guidance from the production schedule generated by the ICOGO model.

4.4.5. MILGP Cut-Off Grade Constraints

The optimum cut-off grade profile was generated by the ICOGO model. Here, the cut-off grade values for each period are used to control the grade of the material that can be sent to the processing destination in each period. From Equation (29), if the grade of the mining-cut *K* is less than the optimum cut-off grade in period *t*, then mining-cut *K* cannot be sent to the processing destination in period *t*. Equation (30) controls the grade of material that can be sent to the stockpile in each period. Based on this equation, if the grade of mining-cut *K* is higher than the optimum cut-off grade of period *t* or is less than the minimum acceptable grade, mining-cut *K* cannot be sent to the stockpile in period *t*.

$$x_k^{c,t}\le 0 \qquad \forall\ \mathrm{g}_k^e < g_{opt}^{c,t,e} \tag{29}$$

$$x_{k,s}^{c,t} \leq 0 \qquad \forall\ g_k^e \geq g_{opt}^{c,t,e} \ \ or \ \ g_k^e < g_l \tag{30}$$

4.4.6. MILGP Fines Blending Constraints

To control the quality of material sent to dyke construction destinations, materials should meet the fines requirements. The ore material sent to the processing destination should have the quality required at the processing destination in terms of bitumen and fines. Inequality Equations (31) and (32) ensure that the ore material sent to the processing destination is between the minimum and maximum fines requirements. Equations (33) and (34) verify the same requirements for the ore material that has been sent to the stockpile, since they will be processed in subsequent years. Based on the dyke construction requirements, IB dyke material should have the required fines content. Inequality Equations (35) and (36) guarantee that the IB dyke material sent to the different dyke construction destinations have between the minimum and maximum fines requirements.

$$\underline{fi}^{c,t,e} \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k x_k^{c,t} \right) - \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k fi_k^e x_k^{c,t} \right) \leq 0 \tag{31}$$

$$\sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k fi_k^e x_k^{c,t} \right) - \overline{fi}^{c,t,e} \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k x_k^{c,t} \right) \leq 0 \tag{32}$$

$$\underline{fi}^{c,t,e} \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k x_{k,s}^{c,t} \right) - \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k fi_k^e x_{k,s}^{c,t} \right) \leq 0 \tag{33}$$

$$\sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k fi_k^e x_{k,s}^{c,t} \right) - \overline{fi}^{c,t,e} \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} o_k x_{k,s}^{c,t} \right) \leq 0 \tag{34}$$

$$\underline{fi}^{d,t,\mathrm{id}} \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} id_k n_k^{d,t} \right) - \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} id_k fi_k^{id} n_k^{d,t} \right) \leq 0 \tag{35}$$

$$\sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} id_k fi_k^{id} n_k^{d,t} \right) - \overline{fi}^{d,t,\mathrm{id}} \sum_{p=1}^{P} \left(\sum_{\substack{k \in C_p \\ p \in C_m}} id_k n_k^{d,t} \right) \leq 0 \tag{36}$$

4.4.7. MILGP Mining-Panels Extraction Precedence Constraints

Mining-panels have been used to reduce the number of integer variables and to help solve the optimization problems in a more efficient manner. Mining-panels also provide good minimum mining width for the large cable shovels and trucks used in oil sands mining.

In order to control the mining-panels extraction precedence, a set of binary integer variables, $\left(b_p^t \in [0,1]\right)$ are used. If the extraction of mining-panels p has started in or by period t, b_p^t is equal to one, otherwise, it is zero. Equation (37) ensures that all the immediate preceding mining-panels above mining-panel p are extracted before mining-panel p can be extracted. $F_p\left(L\right)$ is the set containing all the immediate predecessor mining-panels above mining-panel p. Equation (38) ensures that all the immediate preceding mining-panels in the horizontal mining direction of mining-panel p are extracted before mining-panel p can be extracted. $R_p\left(Z\right)$ is the set containing all the immediate preceding mining-panels in the horizontal mining direction, preceding mining-panel p. Equation (39) ensures that before mining-panel p can be extracted, all the immediate predecessor mining-panels in a mining phase, are extracted. $C_m\left(H\right)$ is the set containing all the immediate preceding mining-panels to mining-panel p in a mining phase. Equation (40) ensures that if mining-panel p has not been extracted in previous periods, then the extraction of mining-panel p can start. Equation (41) ensures that if mining-panel p extraction starts in period t, then mining-panel p will be available for extraction in subsequent periods.

$$b_p^t - \sum_{v=1}^{l}\sum_{i=1}^{t} y_w^{v,i} \le 0 \qquad w \in F_p(L) \tag{37}$$

$$b_p^t - \sum_{v=1}^{l}\sum_{i=1}^{t} y_j^{v,i} \le 0 \qquad j \in R_p(Z) \tag{38}$$

$$b_p^t - \sum_{v=1}^{l}\sum_{i=1}^{t} y_g^{v,i} \le 0 \qquad g \in C_m(H) \tag{39}$$

$$\sum_{v=1}^{l}\sum_{i=1}^{t} y_p^{v,i} - b_p^t \le 0 \tag{40}$$

$$b_p^t - b_p^{t+1} \le 0 \tag{41}$$

4.4.8. MILGP Variables Control Constraints

In the MILGP model, the decision variables logics are controlled by applying the variables control constraints, ensuring the requirements of each variable are met. Inequality Equation (42) ensures that the material mined as ore and dyke material from mining-cuts belonging to mining-panel p in period t are less or equal to the total material mined from mining-panel p in period t from any mining location. Equation (43) is a reserve constraint that ensures that the total available ore in each mining phase will be mined. This facilitates in-pit tailings deposition once a phase is completely extracted. Inequality Equations (44) to (47) ensure that the summation of the portions of the mining-panels and mining-cuts scheduled for different destinations in different periods are less than or equal to one. Since the TCS dyke material is produced from processed ore, Equation (48) ensures that the fraction of TCS scheduled in each period is less than or equal to the fraction of ore processed in that period.

$$\sum_{d=1}^{D}\sum_{s=1}^{S}\sum_{c=1}^{C}\sum_{\substack{k\in C_p\\ p\in C_m}} \left(o_k x_k^{c,t} + o_k x_{k,s}^{c,t} + od_k u_k^{d,t} + id_k n_k^{d,t}\right) \le \sum_{l=1}^{L}\sum_{p\in C_m}\left[y_p^{l,t}\left(o_p + od_p + id_p + w_p\right)\right] \tag{42}$$

$$\sum_{s=1}^{S}\sum_{c=1}^{C}\sum_{t=1}^{T} x_k^{c,t} + x_{k,s}^{c,t} = 1 \tag{43}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T} y_p^{d,t} \le 1 \tag{44}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T} u_k^{d,t} \le 1 \tag{45}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T} n_k^{d,t} \le 1 \tag{46}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T} z_k^{d,t} \leq 1 \tag{47}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T} z_k^{d,t} \leq \sum_{c=1}^{C}\sum_{t=1}^{T} x_k^{c,t} + \sum_{s=1}^{S}\sum_{t=1}^{T} x_k^{s,t-kd} \qquad t-kd>0 \tag{48}$$

4.4.9. MILGP Non-Negativity Constraints

Equation (49) ensures that the decision variables for mining, processing, stockpiling, OB, IB and TCS dyke material cannot be negative. To support the goal functions, Equation (50) also ensures that the deviational variables cannot be negative.

$$y_p^{l,t},\, x_k^{c,t},\, x_{k,s}^{c,t},\, u_k^{d,t},\, n_k^{d,t},\, z_k^{d,t} \geq 0 \tag{49}$$

$$gd_1^{-,l,t},\, gd_2^{-,c,t},\, gd_3^{-,d,t},\, gd_4^{-,d,t},\, gd_5^{-,d,t},\, gd_6^{-,c,t},\, gd_7^{+,c,t} \geq 0 \tag{50}$$

5. Application to an oil sands deposit

The ICOGO model and the MILGP framework discussed in Section 4 are applied to an oil sands case study. Different stockpiling scenarios were investigated to assess the impact of the stockpiling duration on the mining operation. The final pit limit was considered to have three main pushbacks for phased mining. The horizontal mining precedence is defined based on these three main pushbacks. Figure 5 shows the three pushbacks within the final pit limit and the bitumen grade distribution on level 302.5 m.

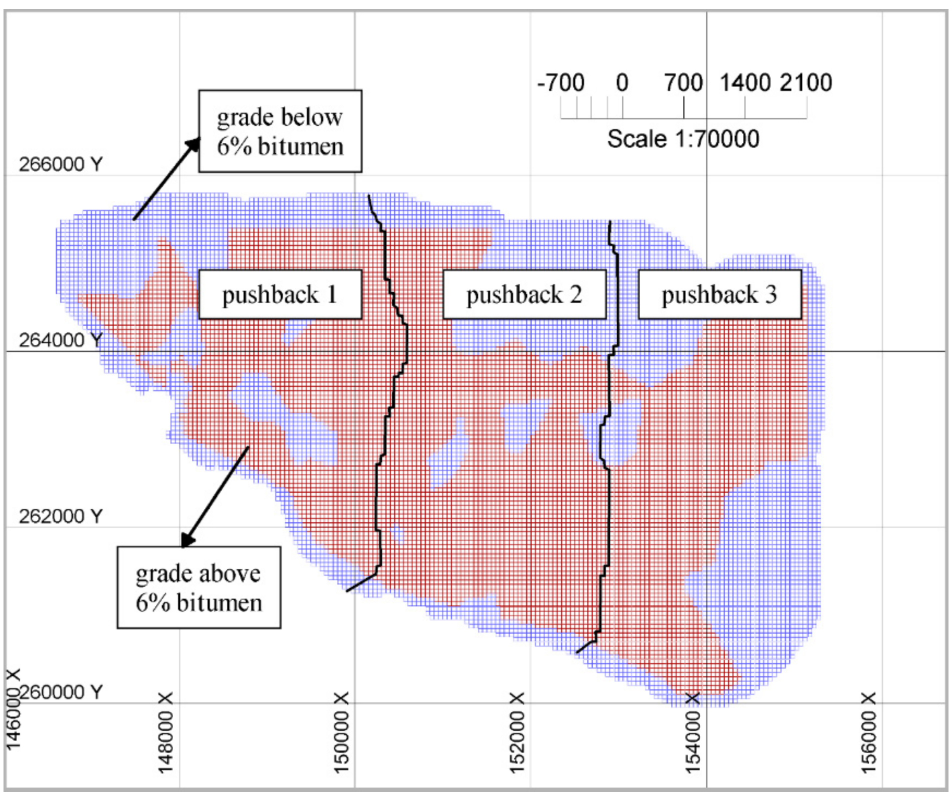

Figure 5: Pushbacks and bitumen grade distribution in the case study area on level 302.5 m

Table 1 contains information about the oil sands deposit for the case study and Table 2 shows the economic data extracted and compiled from Ben-Awuah (2013) and Burt et al. (2012). Since all the input parameters are considered to be deterministic, a discount rate of 15% is used to factor in the risks associated with the development of oil sands resources.

Table 1: Oil sands deposit pushbacks and final pit characteristics

Description	Value			
	Pushback 1	Pushback 2	Pushback 3	Final pit (Total)
Total tonnage of material (Mt)	1989.3	2294.6	2246.3	6530.2
Total ore tonnage (Mt)	695.4	875.8	728.4	2299.6
Total TCS dyke material tonnage (Mt)	476.1	582.4	573.5	1632.0
Total OB dyke material tonnage (Mt)	600.7	676.8	595.2	1872.7
Total IB dyke material tonnage (Mt)	448.3	579.3	600.7	1628.4
Total waste tonnage (Mt)	244.8	162.6	321.9	729.3
Number of blocks	26,334	30,129	28,706	85,169
Number of mining-cuts	754	858	814	2,426
Number of mining-panels	45	41	39	125
Number of mining benches	9	9	9	9

Table 2: Economic parameters (Ben-Awuah, (2013); Burt et al., (2012))

Parameter	Value
Mining cost ($/tonne)	2.5
Processing cost ($/tonne)	5.03
Stockpiling cost ($/tonne)	0.5
TCS dyke material cost ($/tonne)	0.92
OB dyke material cost ($/tonne)	0.95
IB dyke material cost ($/tonne)	0.95
Selling price ($/bitumen %mass)	4.5
Annual fixed cost (M$/year)	1,590
Discount rate (%)	15

The ICOGO model was coded in Matlab (Mathworks, 2015) and implemented on the oil sands deposit. The model was implemented based on two stockpiling management scenarios: Scenario 1a) reclaiming stockpile simultaneously with the mining operation after one year duration and Scenario 2a) reclaiming stockpile simultaneously with the mining operation after two years duration. The optimization problem was solved in 2.2 seconds for Scenario 1a and 1.9 seconds for Scenario 2a. Figures 6 and 7 show the production schedule and average head grade for Scenario 2a. Details of the implementation of the ICOGO model for the case study have been documented in Seyed Hosseini (2017). The cut-off grade profile, average head grade and production schedule generated by the ICOGO model are used as a guide for setting up the MILGP mine planning model requirements.

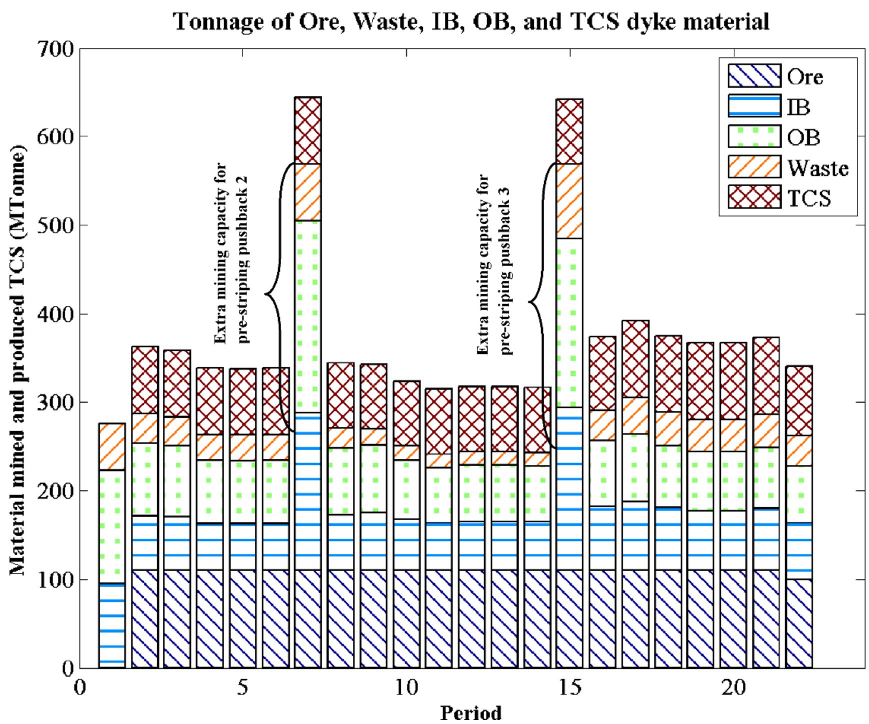

Figure 6: Schedule for material mined, processed and produced TCS for Scenario 2a

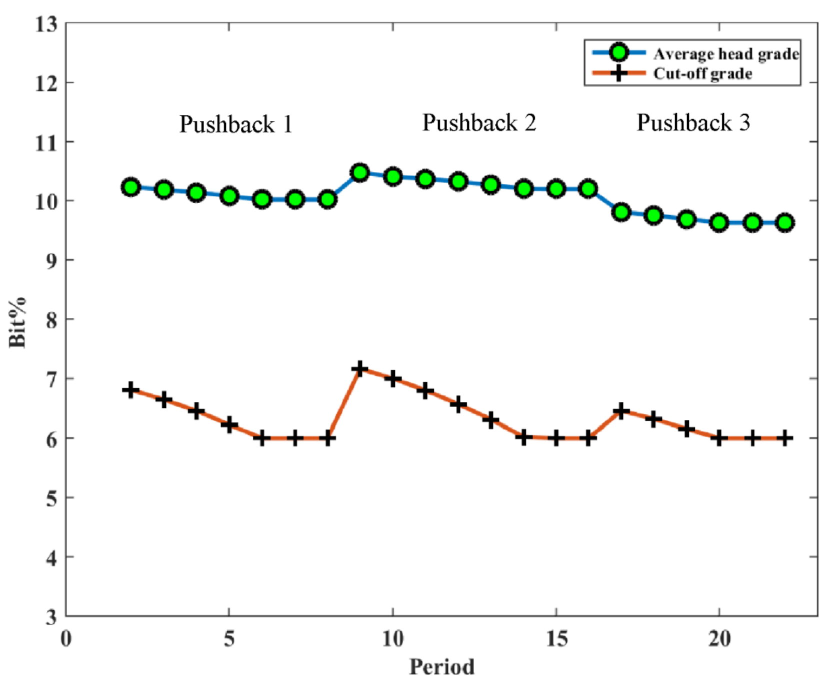

Figure 7: Average head grade and cut-off grade profile for Scenario 2a

The MILGP model was implemented in Matlab (Mathworks, 2015) and IBM CPLEX (IBM ILOG, 2012) was used as the optimization solver. IBM CPLEX (IBM ILOG, 2012) uses the branch-and-cut algorithm which is a hybrid of branch-and-bound algorithm and cutting plane methods to solve the optimization problem. The termination criterion, which is known as the gap tolerance (EPGAP), needs to be set by the user. EPGAP sets a relative tolerance on the gap between the best integer objective and the objective of the best node remaining in the branch-and-cut algorithm. CPLEX will terminate the optimization process when a feasible integer solution within the set EPGAP has been reached. An EPGAP of 10% was set as the termination criterion for the optimization process. The MILGP model was implemented on a Lenovo P510 computer with Intel Xeon (E5) at 3.6 GHz with 64 GB RAM. The optimization problem was solved in 108.2 hours for the scenario with one year stockpile duration (Scenario 1b) and 58.1 hours for the scenario with two years stockpile duration (Scenario 2b).

5.1. Discussion of Results: Scenario 2b

One of the main advantages of the MILGP model is the ability to setup production goals with allowable deviational variables which ensures that a feasible solution can be achieved each time whereas an infeasible solution will have been reported for other mathematical programming frameworks. The prioritized penalty parameters provide options for planners to ensure some goals are closely achieved over others. Different goals were defined based on mine management requirements. In the case study, one of the main objectives is to get a uniform ore production rate for the processing plant.

Figure 8 shows the schedule for material mined, processed, and OB, IB and TCS dyke material for different dyke construction destinations for Scenario 2b. The MILGP model generated an NPV of \$6,014.9 M for the life of mine including the waste management cost for Scenario 2b. A summary of the numerical results from the MILGP model can be seen in Table 3.

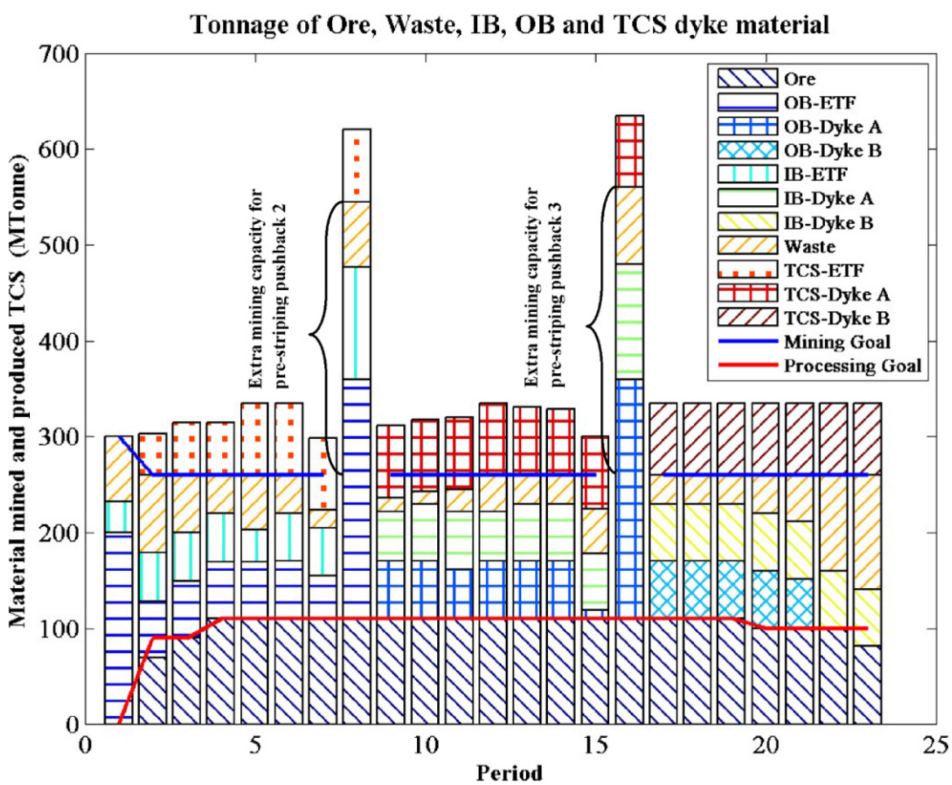

Figure 8: Schedule for material mined, processed and produced TCS for Scenario 2b

Table 3: Numerical results from the MILGP model

Stockpile management scenario	Total material mined (Mt)	Total material Processed (Mt)	Material processed from stockpile (Mt)	Total dyke Material (Mt)	NPV (M$)
Scenario 1b: Reclamation after 1 year	6,501.0	2,299.6	43.8	4,666.2	5,950.4
Scenario 2b: Reclamation after 2 years	6,478.2	2,299.6	42.7	4,641.8	6,014.9

From the production schedule, pre-stripping was enforced in year one and the preferred processing target in year two had to be adjusted. This was due to the location of ore material in the pit and mining precedence of the mining-cuts. The ICOGO model does not take into consideration the actual mining precedence of mining-cuts and hence generated a production target which was unachievable in year two. In the remaining years, all processing targets were achieved until the last year when the ore material was finished. The ore production target starts with 90 Mt and then ramps up to a maximum capacity of 110 Mt. In the last four years, the target is reduced to 100 Mt. Figure 9 shows the stockpile material scheduled for processing in Scenario 2b. The stockpile schedule shows that all material sent to stockpile in any year is fully reclaimed after two years duration. In the MILGP model, the average bitumen head grade is calculated based on the mining-cuts that are processed directly from the mine and reclaimed from the stockpile in each period, taking into consideration the practical mining-cut extraction sequencing. Figure 10 shows the average bitumen head grade target for each period and the scheduled average bitumen head grade with the MILGP model for Scenario 2b. It can be seen that the average bitumen head grade generated by the MILGP model fluctuates around the target provided by the ICOGO model for the most part. Figure 11 illustrates the mining sequence on level 302.5 m for Scenario 2b.

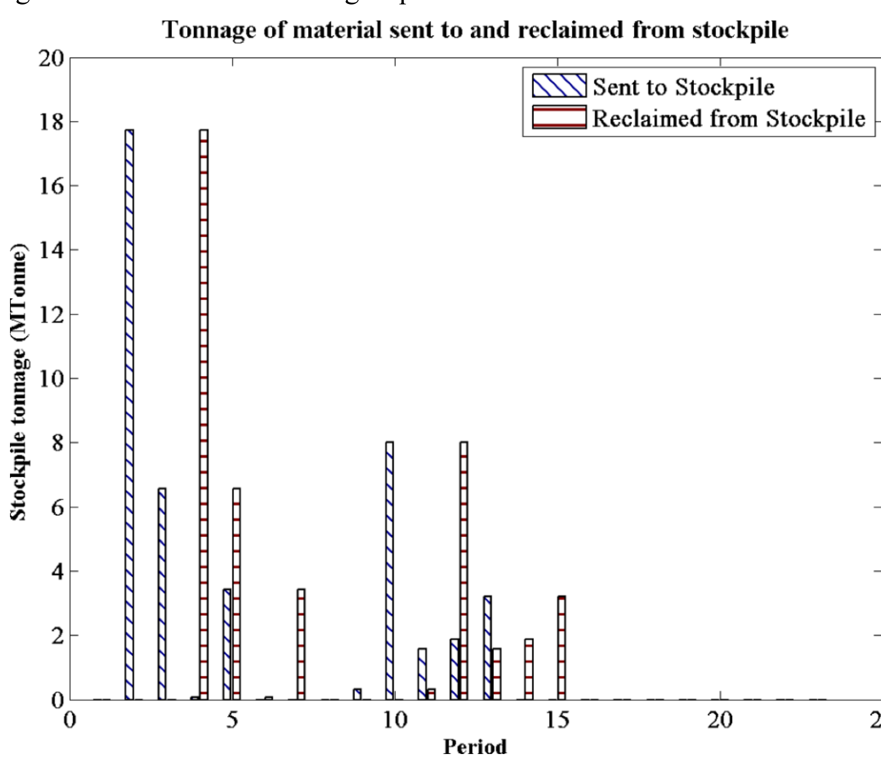

Figure 9: Schedule for material stockpiled and reclaimed after two years in Scenario 2b

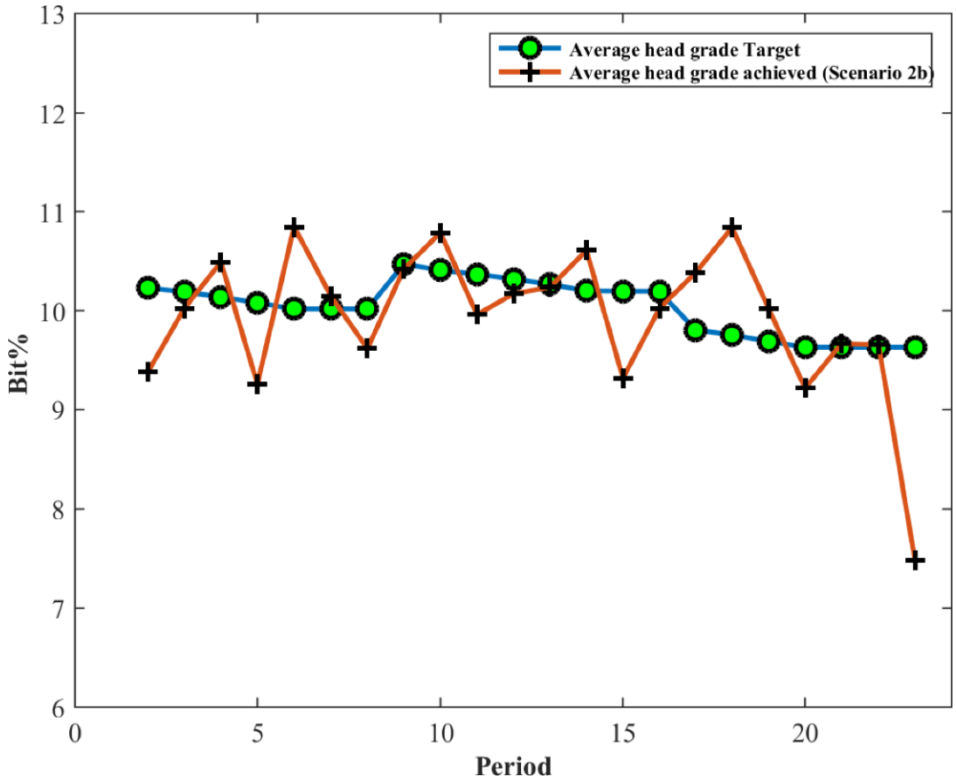

Figure 10: Average bitumen head grade for Scenario 2b

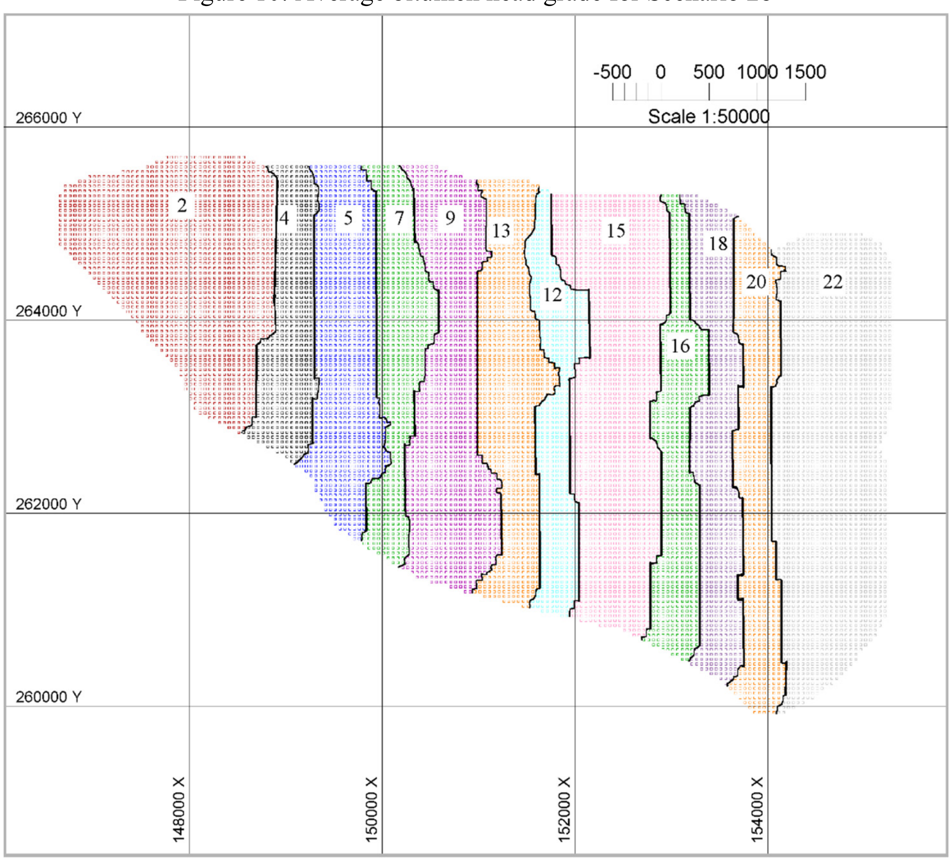

Figure 11: Mining sequence on level 302.5 m for Scenario 2b

5.2. Comparative Experiment

In the previous experiments (Scenarios 1b and 2b), the production schedule and average head grade generated by the ICOGO model were used as inputs to setup targets for the MILGP goal functions. In order to evaluate the impact of the average head grade target provided by the ICOGO model, another optimization experiment (Scenario 3) was conducted by replacing the average head grade goal function (Equation (28)) with Equation (51). Equation (51) specifies the average head grade limiting bounds for ore processing.

$$\underline{g}^{c,t,e} \leq \frac{\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k g_k^e x_k^{c,t}\right)+\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k g_k^e x_{k,s}^{c,t-kd}\right)}{\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k x_k^{c,t}\right)+\sum_{p=1}^{P}\left(\sum_{\substack{k\in C_p \\ p\in C_m}} o_k x_{k,s}^{c,t-kd}\right)} \leq \overline{g}^{c,t,e} \tag{51}$$

These experiments were run to 10% EPGAP and were designed to highlight the impact of the two-step approach on the solution time. For the case study investigated, the new optimization problem (Scenario 3) was solved in 87.2 hours compared to 58.1 hours for Scenario 2b. This comparative analysis showed that using the initial results provided by the ICOGO model to setup a goal function limits the solution space thereby causing the near-optimal solution to be reached faster. The two-step approach improved the solution time by about 33%. Table 4 shows a summary of the results from the comparative experiment.

Table 4: Summary results for comparative experiment

Experiment	Number of constraints	Number of continuous variables	Number of binary variables	Solution time (hrs)	NPV (M$)
Scenario 2b	152,764	845,710	8,372	58.1	6,014.9
Scenario 3	152,787	845,664	8,372	87.2	5,975.3

6. Conclusion

Long-term production scheduling optimization is one of the important aspects of mine planning. In achieving the maximum benefit from a mining operation, the long-term production schedule should detail the time and sequence of removing ore and waste material from the final pit limit. Improving the efficiency of production scheduling optimization tools' performance in the mining industry is a high priority task since the economic gains are considerably high.

In the case of oil sands mining, the waste management strategy drives the sustainability and profitability of the mining operation. It makes it necessary to consider the waste management cost and its constraints in the cut-off grade optimization process for integrated long-term production scheduling. In this research, the ICOGO model which is based on a fast heuristic optimization framework was developed. The ICOGO model determines the optimum cut-off grade policy taking into consideration stockpiling with limited duration, and waste management costs for dyke construction. Subsequently, the cut-off grade profile, average head grade and production schedule generated by the ICOGO model were used as guides in setting up the inputs for the MILGP model.

The MILGP model generates a more practical and detailed schedule for extracting ore, waste and dyke material from the final pit limit. The MILGP model provides simultaneous stockpile reclamation with the specified stockpiling duration taking into consideration processing recovery changes resulting from oxidation of stockpiled ore. The MILGP model provides a framework consistent for sustainable oil sands mining with respect to regulatory requirements. Table 3 presents a summary of the MILGP model results for Scenarios 1b and 2b. The NPV generated by Scenario 2b was 1% higher than Scenario 1b. This increase in NPV is due to different dyke material tonnages scheduled and the flexibility in stockpiling and reclamation in Scenario 2b allowing the optimizer to send higher grades for processing in early years to generate more profit.

Although the level of detail of the production schedule generated by the ICOGO model is not similar to the MILGP model, it provides an initial production schedule for the life of mine planning. The results from the ICOGO model can be used as a guide for detailed long-, medium-, and short-term mine planning with any production scheduling optimization framework. It should be mentioned that the main advantage of the ICOGO model over the MILGP model is the significantly less solution time. For the case study investigated, the ICOGO model was solved in less than 3 seconds whereas the MILGP model required 58.1 hours to solve on a Lenovo P510 computer with Intel Xeon (E5) at 3.6 GHz with 64 GB of RAM. In conclusion, whereas the ICOGO model solved the optimization problem faster, the MILGP model results provide detailed mining-cut extraction sequencing for practical mining.

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8. Appendix

Indices and Sets

$c \in C$, $\mathrm{C} = \{1,2,......,\mathrm{C}\}$ index and set for all the possible processing destinations.

$d \in D$, $\mathrm{D} = \{1,2,......,\mathrm{D}\}$ index and set for all the possible destinations for materials.

$e \in \mathrm{E}$, $\mathrm{E} = \{1,2,......,\mathrm{E}\}$ index and set for all the elements of interest in each mining-cut.

$k \in \mathrm{K}$, $\mathrm{K} = \{1,2,......,\mathrm{K}\}$ index and set for mining-cuts.

$l \in \mathrm{L}$, $\mathrm{L} = \{1,2,......,\mathrm{L}\}$ index and set for all the possible mining location.

$m \in \mathrm{M}$, $\mathrm{M} = \{1,2,......,\mathrm{M}\}$ index and set for all the phases (pushbacks).

$p \in \mathrm{P}$, $\mathrm{P} = \{1,2,......,\mathrm{P}\}$ index and set for mining-panels.

$t \in \mathrm{T}$, $\mathrm{T} = \{1,2,......,\mathrm{T}\}$ index and set for all the scheduling periods.

$s \in S$, $\mathrm{S} = \{1,2,......,\mathrm{S}\}$ index and set for all stockpiles.

$C_p(V)$ for each mining-panel p, there is a set $C_p(V) \subset \mathrm{K}$ defining the mining-cuts that belongs to the mining panel p, where V is the total number of mining-cuts in the set $C_p(V)$.

$C_m(H)$ for each phase m, there is a set $C_m(H) \subset \mathrm{P}$ defining the mining-panels within the immediate predecessor pit phases (pushbacks) that must be extracted prior to extracting phase m, where H is an integer number representing the total number of mining panels in the set $C_m(H)$.

$F_p(L)$ for each mining-panel p, there is a set $F_p(L) \subset \mathrm{P}$ defining the immediate predecessor mining-panels above mining-panel p that must be extracted prior to extraction of mining-panel p, where L is the total number of mining-panels in the set $F_p(L)$.

$R_p(Z)$ for each mining-panel p, there is a set $R_p(Z) \subset \mathrm{P}$ defining the immediate predecessor mining-panels in a specified horizontal mining direction that must be extracted prior to extraction of mining-panel p at the specified level, where Z is the total number of mining-panels in the set $R_p(Z)$.

Decision variables

$b_p^t \in [0,1]$**,** a binary integer variable controlling the precedence of extraction of mining-panels. If the extraction of mining-panel p has started by or in period t, b_p^t is equal to one, otherwise it is zero.

$gd_1^{-,l,t}$**,** the amount of negative deviation from the mining target (tonnes) at location l in period t.

$gd_2^{-,c,t}$**,** the amount of negative deviation from the processing target (tonnes) at processing destination c in period t.

$gd_3^{-,d,t}, gd_4^{-,d,t}, gd_5^{-,d,t}$**,** the amount of negative deviation from the overburden, interburden and tailings coarse sand dyke material target (tonnes) at destination d in period t, respectively.

$gd_6^{-,c,t}$, the amount of negative deviation from average head grade target (%mass) at processing destination c in period t.

$gd_6^{+,c,t}$, the amount of positive deviation from average head grade target (%mass) at processing destination c in period t.

$n_k^{d,t}, u_k^{d,t}, z_k^{d,t} \in [0,1]$, a continuous variable representing the interburden, overburden and tailings coarse sand dyke material portion of mining-cut k to be extracted and used for dyke construction at destination d in period t, respectively.

$x_k^{c,t} \in [0,1]$, a continuous variable representing the ore portion of mining-cut k to be extracted and processed at destination c in period t.

$x_{k,s}^{c,t} \in [0,1]$, a continuous variable representing the ore portion of mining-cut k to be extracted and sent to stockpile s in period $t-kd$ and reclaimed to be processed at destination c in period t.

$y_p^{l,t} \in [0,1]$, a continuous variable representing the ore portion of mining-panel p to be mined in period t from location l, which includes ore, overburden and interburden dyke material and waste from the associated mining-cuts.

Parameters

bc, the cost per tonne of overburden dyke material for dyke construction.

$bc^{d,t}$, the cost in present value terms per tonne of overburden dyke material for dyke construction at destination d.

$c_k^{l,t}, c_p^{l,t}$, the discounted cost of mining all the material in mining-cut k and mining-panel p as waste from location l in period t, respectively.

$d_k^{d,t}$, the discounted economic mining-cut value obtained by extracting mining-cut k and sending it to destination d in period t.

$d_{k,s}^{d,t}$, the discounted economic mining-cut value obtained by extracting mining-cut k and sending it to stockpile s and reclaiming it to destination d in period t.

$ei_k^{d,t}, eo_k^{d,t}, et_k^{d,t}$, the extra discounted cost of mining all the material in mining-cut k as interburden, overburden and tailings coarse sand dyke material for construction at destination d in period t, respectively.

F, the annual fixed cost.

F^t, the discounted annual fixed cost in period t.

fi_k^e, the average percent of fines in ore portion of mining-cut k.

$\underline{fi}^{c,t,e}, \overline{fi}^{c,t,e}$, the lower and upper bound on the required average fines percent of ore at processing destination c in period t.

fi_k^{id}, the average percent of fines in interburden dyke material portion of mining-cut k.

$\underline{fi}^{d,t,id}, \overline{fi}^{d,t,id}$, the lower and upper bound on the required average fines percent of interburden dyke material at dyke construction destination d in period t.

g_{avg_n}, the average head grade.

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

$g_{opt}^{c,t,e}$, the cut-off grade of element e at processing destination c in period t.

g_p, the processing limited cut-off grade.

$\underline{g}^{c,t,e}, \overline{g}^{c,t,e}$, the lower and upper bound on the required average bitumen head grade of ore at processing destination c in period t

$HT^{c,t}$, the average head grade target at processing destination c in period t.

i, the discount rate.

ic, the cost per tonne of interburden dyke material for dyke construction.

$ic^{d,t}$, the cost in present value terms per tonne of interburden dyke material for dyke construction at destination d.

id_k, id_p, the interburden dyke material tonnage in mining-cut k and in mining-panel p, respectively.

$IT^{d,t}$, the interburden dyke material target (tonnes) at destination d in period t.

$kc_s^{c,e,t}$, the extra cost in present value terms per tonne of ore for re-handling from stockpile s and processing at processing destination c in period t.

kd, the duration of stockpiling the material.

kt_n, the amount of material (tonnes) sent to the stockpile in each period.

mc, the cost of mining a tonne of waste.

$mc^{l,t}$, the cost in present value terms of mining a tonne of waste in period t from location l.

$MT^{l,t}$, the mining target (tonnes) at location l in period t.

o_k, o_p, the ore tonnage in mining-cut k and in mining-panel p, respectively.

od_k, od_p, the overburden dyke material tonnage in mining-cut k and in mining-panel p, respectively.

$OT^{d,t}$, the overburden dyke material target (tonnes) at destination d in period t.

pc, the extra cost per tonne of ore for mining and processing.

$pc^{c,e,t}$, the extra cost in present value terms per tonne of ore for mining and processing at processing destination c in period t.

$PP_1, PP_2, PP_3, PP_4, PP_5$, the prioritize penalty parameter associated with the deviation from the mining target, processing target, overburden, interburden and tailing coarse sand dyke material target, respectively.

PP_6, PP_7, the prioritize penalty parameter associated with the deviation from the average head grade target.

pr_n, the annual profit.

$PT^{c,t}$, the processing target (tonnes) at processing destination c in period t.

qm, the amount of material to be mined (tonnes)

QP, the maximum processing capacity in terms of tonnes per year

qp, the amount of material to be processed (tonnes)

qr, the amount of material to be refined (tonnes)

r_{avg}, the weighted average processing recovery factor.

$r_{avg}^{c,e}$, the proportion of element e recovered if it is processed at processing destination c (weighted average processing recovery).

$r_{avg,s}^{c,e}$, the proportion of element e recovered if it is reclaimed from stockpile s and processed at processing destination c (weighted average processing recovery).

R_{IB}, the ratio of the total amount of interburden dyke material over the total amount of waste material.

R_{OB}, the ratio of the total amount of overburden dyke material over the total amount of waste material.

R_{TCS}, the ratio of the total amount of tailings coarse sand dyke material over the total amount of ore material.

sp, the selling price per unit of product.

$sp^{e,t}$, the selling price of element e in present value terms per unit of product.

sc, the refinery and selling cost per unit of product.

$sc^{e,t}$, the refinery and selling cost of element e in present value terms per unit of product.

$sv_{k,s}^{c,t}$, the discounted revenue obtained by selling the final products within mining-cut k if it is sent to processing destination c in period t from stockpile s, minus the extra discounted cost of mining all the material in mining-cut k as ore from location l and processing at processing destination c; minus the extra discounted cost of re-handling for stockpile material; and minus the discounted annual fixed cost.

tc, the cost per tonne of tailings coarse sand dyke material for dyke construction.

$tc^{d,t}$, the cost in present value terms per tonne of tailings coarse sand dyke material for dyke construction at destination d.

td_k, the tailings coarse sand dyke material tonnage in mining-cut k.

$TT^{d,t}$, the tailings coarse sand dyke material dyke material target (tonnes) at destination d in period t.

$v_k^{c,t}$, the discounted revenue obtained by selling the final products within mining-cut k if it is sent to processing destination c in period t, minus the extra discounted cost of mining all the material in mining-cut k as ore from location l and processing at processing destination c; and minus the discounted annual fixed cost

w_k, w_p, the waste tonnage in mining-cut k and the waste tonnage in mining-panel p, respectively.

A review of models and algorithms for strategic mining options optimization

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Abstract

In major mining projects, deviations from optimal mine plans will result in significant financial losses, future financial liabilities, delayed reclamation and resource sterilization. It is important that the strategic mine plan makes optimum use of available resources and provide continuous quality ore to drive sustainable mining and profitability. This requires the development of a well-integrated strategy of mining options for open pit and/or underground mining and their interactions. However, current tools and methodologies used in the mining industry are not adequate in dealing with the complexity of subjecting a deposit to rigorous stochastic mining options optimization with a measure of optimality. Development of innovative technologies, quantification of uncertainty and optimization in strategic mine planning plays a significant role in reducing financial risk and environmental footprints, and promoting sustainable development through improved resource governance and total mine reconciliation. This research reviews existing models and algorithms that evaluate open pit and/or underground mining options optimization. Extensive literature review and gap analysis matrix are used to identify the associated limitations, and opportunities for improvement are outlined.

1. Introduction

Mining is the process of extracting a beneficial naturally occurring resource from the earth crust (Caro et al., 2007; Newman et al., 2010). When an orebody extends from surface to 'great depth', the part of the orebody close to the surface is usually mined with an open pit (OP) to generate early revenue, while the deeper part is subsequently extracted using a cheaper underground (UG) mining alternative (Opoku and Musingwini, 2013) to reduce stripping ratio. As open pit mining deepens, the stripping ratio typically increases, increasing the overall mining cost. As a result, companies often strategically transition between surface and underground to maximize project value and increase resource extraction ratio (Breed, 2016). Fig. 1 is a schematic representation of strategic mining options or the transition problem from open pit to underground mining. The term mining options optimization has been used by researchers and professionals to refer to the initiatives or choices undertaken in the extractive industry to expand, change, defer, abandon and adopt strategies for a mining method(s) and sometimes investment opportunities; based on changing economic, technological or market conditions (Shinobe, 1997; Bakhtavar et al., 2007; Bakhtavar et al., 2008; Bakhtavar et al., 2009; Roberts et al., 2009; Brady and Brown, 2012; Opoku and Musingwini, 2013; Roberts et al., 2013; Ben-Awuah et al., 2016; Marketwired, 2016; Inc., 2017).

Open pit mining usually features a relatively lower mining cost, higher stripping ratio and longer time to access ore (Koushavand et al., 2014; Ben-Awuah et al., 2016) while underground mining on the other hand features a higher mining cost, higher grade and earlier access to ore (Anthony, 2012; Pourrahimian et al., 2013; Terblanche and Bley, 2015; Ben-Awuah et al., 2016). Late stage cut-backs in open pit mining are generally more expensive than earlier stages, but underground mining costs are less likely to rise as much with depth. These late stage cutbacks often have long lead times between waste mining and ore extraction, and the discounting effect of the cash flows must be considered (Earl, 2013).

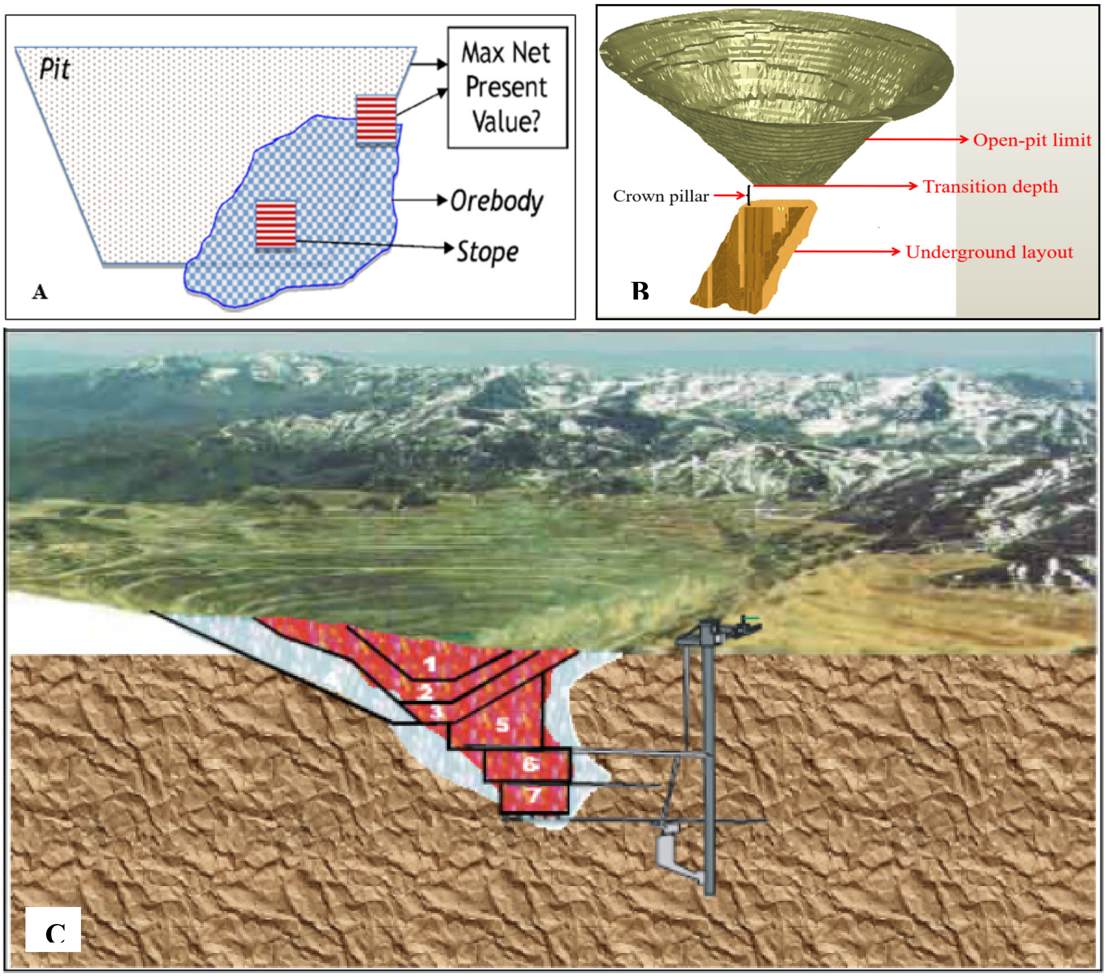

Fig. 1 Schematic representation of strategic mining options or the transition problem from open pit to underground mining [A – Ben-Awuah et al. (2016); B – Oraee and Bakhtavar (2010); C – King (2000)]

The problem of optimizing reserve exploitation depends largely on the mining option used in the extraction. Some mineral deposits have orebodies that extend from near the surface to several meters in depth. Such deposits can be amenable to either open pit mining or underground mining or both, in different variations and forms. This paper reviews relevant literature on algorithms and models for open pit – underground mining options optimization, and further identifies gaps and opportunities that can be explored for further research and implementation in the mining industry.

2. Summary of Literature Review

Based on the geometry and orientation of the orebody, open pit mining becomes more favorable than underground mining or vice versa or both. There is a depth within the mineralized zone where comparisons are made between ore extraction using surface mining methods or underground mining methods or both. This depth is broadly referred to as the transition depth or transition interface or cut-over point. According to Opoku and Musingwini (2013), the transition point is often determined anytime from project pre-feasibility stage to several years after commencement of the mining operation. Bakhtavar et al. (2009) commented that, the most sensitive problem for a deposit that has the potential to be mined by a combined method of open pit and underground is the determination of the optimal transition depth from open-pit to underground or vice versa.

Current strategic open pit and underground mining interface optimization models have been developed mainly based on determining the transition point or depth between open pit mining and underground mining. These models mainly focus on investigating how an underground mining operation can be exploited after an open pit mine or combined with an existing open pit operation. (Ben-Awuah et al., 2016). Acknowledging notable challenges and shortfalls, several researchers have employed techniques, algorithms and/or models to determine the transition depth (Bakhtavar et al., 2009; Opoku and Musingwini, 2013; Roberts et al., 2013; Dagdelen and Traore, 2014; Ordin and Vasil'ev, 2014; De Carli and de Lemos, 2015; King et al., 2016; MacNeil and Dimitrakopoulos, 2017) and the strategy for extracting these ore blocks (De Carli and de Lemos, 2015; Ben-Awuah et al., 2016; King et al., 2016; MacNeil and Dimitrakopoulos, 2017). According to Roberts et al. (2013), optimization of an open pit mine in conjunction with an existing high production underground operation is more complex. This challenge is faced by a growing number of operations throughout Australia and around the world and has not been fully addressed in the literature. Ordin and Vasil'ev (2014), King et al. (2016) and MacNeil and Dimitrakopoulos (2017) have developed mathematical programming models (MPMs) to handle the optimization of an open pit mine in conjunction with an underground mine for a specific orebody.

Available robust, risk-based and practical models and techniques to directly optimize the open pit-underground mining interface and interactions with integrated waste management are currently limited. A stochastic model that comprehensively and simultaneously schedules an optimized open pit mine, determines the transition interface and further schedules an optimized underground mine for an orebody will add significant value to the mining industry. Fig. 2 is a schematic representation of some research studies on the optimization of mining options in literature.

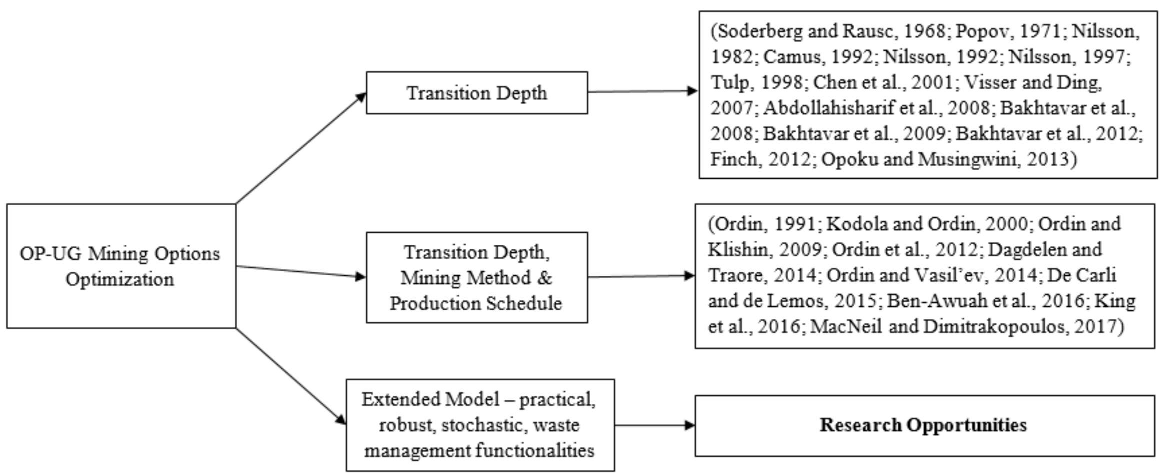

Fig. 2 Schematic representation of some research studies on the optimization of mining options

3. Open pit – underground (OP-UG) mining options

Historical assessment of mineral resource evaluations has demonstrated the sensitivity of project profitability to decisions based on mine planning (Ben-Awuah et al., 2016). Two main kinds of mining method exist when mining options are being considered: sequential and parallel mining. In sequential mining, the economic mineralization is continuous over depths that could be economically extracted by open pit and underground methods. The open pit and underground operations are competing for the same resource. In parallel mining, there is an opportunity to exploit a distinct independent deposit by both open-pit and underground operations simultaneously (Finch, 2012).

Mining options scenarios have been broadly grouped into three: (1) open pit mine to underground mine or underground mine after open pit mine, (2) concurrent open pit mine and underground mine, and (3) underground mine to open pit mine or underground mine after open pit mine. From the mining options above, the transitioning is the main challenge to the mine planner. From a practical point of view, planning for the transition requires a long lead-time as the implications on the ultimate pit and the underground design can be significant. This means that determination of the cut-over point and strategy should be thoroughly examined prior to the commencement of construction (Opoku and Musingwini, 2013). The transition problem is the determination of the optimal transition point with the aim of maximizing the project's value and resource utilization.

The decision to adopt any particularly mining option surely depends mainly on the economics of the project. Earl (2013) explained that, it is important to undertake rigorous analysis and model the transition zone over the widest range of conditions possible. Finch (2012) identified three typical approaches to determining the cut-over point. These are (1) biggest economic pit, (2) incremental undiscounted cashflow, and (3) automated scenario analysis. According to Earl (2013), it is worth exploring all options to reduce unit costs and minimize risk, thus, canceling that big cutback and changing to underground mining may provide one such avenue.

For the biggest economic pit approach, the open pit to underground cut-over is determined by focusing on the economic size of the open pit. Consideration of underground mining is secondary, and it is based on the remaining resource outside this pit. The biggest economic pit is the simplest and most common approach. It can be determined using any one of the several commercially available pit optimization software packages. The pit will terminate at the point that the marginal cost of waste stripping outweighs the marginal revenue generated by additional ore processing. (Finch, 2012).

For the incremental undiscounted cashflow approach, the marginal profit derived from the pit associated with depth decreases with depth. Given that underground mining profits are less dependent on depth, there will likely be a shallower point where the marginal profit of the underground exceeds that of the open pit. Using this method, the cut-over point is the depth at which the marginal profit from the open-pit is equal to the marginal profit from the underground. This is usually shallower than the largest economic pit method. This method can also be undertaken using commercially available software (Finch, 2012).

For the automated scenario analysis approach, the method, unlike the incremental undiscounted cashflow, accounts for discounting. As the underground mine operates at a higher cut-off grade than the open pit, it will deliver a higher grade and normally higher cashflow for the same throughput. Therefore, there is likely a discounted cashflow benefit from generating this cashflow early which may elevate the optimal transition point. The only way to test this is to complete schedules (which include open pit and underground mining) and derive an NPV for each potential transition point. Depending on the complexities of the mine, deriving a new schedule for each transition point can be very time consuming, and to test a reasonable number of transition points in a reasonable time, automated optimizing scheduling software should be used. The software should be able to handle both underground and open pit mine scheduling simultaneously, and should be able to develop an optimized schedule for each transition point. In this way, each schedule generated reflects the best possible schedule for a given transition point. Using this kind of software, a suite of transition points can be evaluated, and their results compared so that the point that offers the highest value can be chosen (Finch, 2012).

In recent researches on the problems of mining options, the automated scenario analysis approach has been employed in several modified ways by Bakhtavar et al. (2012), Opoku and Musingwini (2013), Ordin and Vasil'ev (2014), King et al. (2016) and MacNeil and Dimitrakopoulos (2017). Table 1 shows a matrix comparison of notable research on the OP-UG transition problem for the last decade. Discussions to these modifications have been reviewed in later sections.

Table 1: Notable research on OP-UG transition problem for the past decade

	Name of Author(s)	MacNeil and Dimitrakopoulos	King et al.	Ben-Awuah et al.	De Carli and de Lemos	Ordin and Vasil'ev	Dagdelen and Traore	Roberts et al.	Opoku and Musingwini	Bakhtavar et al.	Bakhtavar et al.
	Year	2017	2016	2016	2015	2014	2014	2013	2013	2012	2009
	Research Focus	Optimal Transition Depth - Instances	Optimal Transition Depth - Instances	Assessment of Transition Problem	Optimal Transition Depth - Instances	Optimal Transition Depth - Dynamic	Optimal Transition Depth	Assessment of Transition Problem	Optimal Transition Depth - Dynamic	Optimal Transition Depth	Optimal Transition Depth
Approach Used	**Algorithm**										Heuristic
	Model	Stochastic Integer Model	MILP	MILP		Dynamic Programming - lag, trend, nonlinear	MILP - OptiMine® used to optimise the transition problem	MILP - OP & UG		(0-1) Integer Programming	
	Software Application			Evaluator	Studio 3 and NPV Scheduler		OptiMine, Whittle, Studio 5D and EPS	Open pit Optimization - Blasor; Open Pit Schedule - COMET; UG Optimization - Evaluator	Open pit Optimization - Whittle; Open Pit Schedule - XPAC; UG Optimization - Datamine's MRO; Excel analysis		
Outputs / Performance / Transition Indicators	**NPV**	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	IRR			Yes	Yes						
	Mining Recovery				Yes						
	Avg. ROM Grade							Yes	Yes		
	Gold Price to Cost Ratio								Yes		
	Production Rate					Yes		Yes	Yes		
	Stripping Ratio				Yes	Yes			Yes		
	Mine Life				Yes	Yes	Yes	Yes			
	Revenue					Yes					
	Mining Cost							Yes			
	Production Schedule	OP & UG		OP, UG & OP-UG		Standalone for OP & UG	Standalone for OP & UG				
	Commodity	Gold		Gold-silver-copper	Gold	Coal mining - kimberlite pipe	Gold	Iron	Gold - 4 different deposits	Hypothetical	
	Notable Remarks	20 simulated grades used. Compared to a deterministic model - 9% better NPV							Deterministic not good		One level assumed as the crown pillar

3.1. Optimization models and algorithms for OP-UG mining options

Identifying the transition depth or interface in the transitional problem and the ore extraction strategy of any mining option study is very strategic. According to Ben-Awuah et al. (2016), the aim of long-term production scheduling is to determine the strategy, thus, the time and sequence of extraction and displacement of ore and waste, that maximizes the overall discounted net present revenue from a mine within the existing economic, technical and environmental constraints. Long-term production schedules define the mining and processing plant capacity, and expansion potential as well as management investment strategy. The problem of optimizing reserve exploitation depends largely on the mining option used in the extraction (Ben-Awuah et al., 2016). Significant value can be generated by rigorously investigating these mining options using optimization tools to arrive at the appropriate strategic plan that maximizes the overall NPV of the deposit (Epstein et al., 2012; Roberts et al., 2013; Ben-Awuah et al., 2016).

Kurppa and Erkkilä (1967) assessed the simultaneous mining between open pit and underground mining during the OP-UG mining at Pyhasalmi mine. They indicated that, the simultaneous mining was possible due to the geometry of the orebody being worked on. Luxford (1997) argued that cost usually drives the decision to make the transition because as the open pit waste stripping cost keeps rising with depth, there comes a time when the underground mining cost will be less than the open pit mining cost. Stacey and Terbrugge (2000) considered the OP-UG transition for an economically designed pit, which they argued, should have slopes that are close to their stability limits so that there is little scope for extending the open pit to greater depths, other than with a pushback. Finch (2012) dwelled much on the transition point evaluation so that the point which offers higher values can be chosen. He noted that, the transition point depends largely on transition indicators which are uncertain over time.

Roberts et al. (2013) followed three-step processes to determine the material that can be mined from underground ahead of the open pit advancement: (1) open pit optimization to determine an optimal open pit only sequence and schedule, (2) underground with open pit optimization to determine the discounted value of each block being mined from the open pit using the schedule generated from the (1). The discounted value was deducted from the potential underground mining value and the underground is optimized on the net objective, and (3) combined open pit and underground optimization is determined by integrating the open pit and underground sequences into an overall project schedule.

When optimizing a schedule for a single mining operation the value ranking of a block for mining is determined by variables such as the net value per ton, net mill return or net smelter return. However, Roberts et al. (2013) used opportunity cost represented by open pit mining to rank the variables, thus, if the discounted value of a block is greater when mined by open pit then it should not be extracted from underground. Therefore, to rank blocks correctly for an optimized underground with open pit strategy, a measure of 'incremental value' (IV) was developed. When considering a single block, the discounted value that the block adds to the overall operation, its IV will be equal to the discounted value when extracted by the underground mine, minus the discounted value of the block if it were to be extracted by the open pit mine (Roberts et al., 2013).

The problem on optimization of the depth for transition from open pit to underground mining and the design capacity of the open pit and underground mine based on the condition of maximum NPV while accounting for the lag factor has been solved using the optimality principle of dynamic programming by Ordin and Vasil'ev (2014). The mine design capacity optimization procedure based on lag modeling has been developed, tested by design institutions such as Giprougol, Kuzbassgiproshakht and Yakutniproalmaz, and used in some projects on open pit and underground mine planning (Ordin, 1991; Kodola and Ordin, 2000; Ordin and Klishin, 2009; Ordin et al., 2012). Ordin and Vasil'ev (2014) used lag models to account for influence of time lags on future profit and allow estimating economic benefit of freezing of investment in the mine construction period

Dagdelen and Traore (2014) used an iterative approach by evaluating a set of selected transition depths through optimizing the life of mine production schedules of both the open pit and underground mines using mixed linear integer programming (MILP) techniques, a mathematical programming model. The authors begin by using Geovia's Whittle software to generate a series of pits which provide an ultimate pit contour. The locations of the ultimate pit and crown pillar provide a basis for the underground mine design. Optimized life of mine production schedule is then created to determine yearly cash flow and resulting NPV. This procedure is repeated for progressively deeper transition depths until the NPV observed in the current iteration is less than what was seen for a previously considered transition depth, at which point the authors conclude that the previously considered depth, with a higher NPV, is optimal (Dagdelen and Traore, 2014). The MILP model categorically factored the different rock types (3) and ore stockpiling (3 – oxide, transition and fresh) in the model.

To assess the mining option to employed, De Carli and de Lemos (2015) used the premise suggested by Bakhtavar et al. (2008) that the overall stripping ratio (OSR) in the deposit must be smaller than the allowable stripping ratio (ASR) for the feasibility of the open pit mining method to underground mining method. The authors used Studio 3 to determine the ultimate optimal pit limit and the NPV Scheduler was used to generate the production schedule of the ultimate pit. By integrating the use of the mining software, the depth of transition was analyzed using cyclical calculation of the Cut of Grade of the ore blocks.

Ben-Awuah et al. (2016) investigate the strategy of mining options for an orebody using a mathematical programming model – mixed integer linear programming (MILP) optimization framework. The purpose of the framework and methodology is to evaluate the financial impacts of applying different mining options separately or concurrently to extract a given orebody. The MILP formulation maximizes the NPV of the reserve when extracted with (1) open pit mining, (2) underground mining, and (3) concurrent open pit and underground mining. According to Ben-Awuah et al. (2016), the production schedule for a combined open pit and underground mining scenario requires that both mining options compete for the same reserve during optimization. This model did not consider the capital expenditure of the projects, equipment requirement and stochasticity of certain parameters of the problem.

King et al. (2016) incorporated crown pillar placement that separates the open pit from the underground mine, and of the sill pillars, i.e., levels left in situ that can grant earlier access to stopes by creating a false bottom in their OP-UG transition studies. King et al. (2016) developed a mathematical programming model based on an ad-hoc branch-and-bound approach that incorporates decomposition methods for solving precedence constrained production scheduling problem (PCPSP) linear programming relaxations, and that includes rounding heuristics. In their model, they first presented a surface extraction formulation, followed by an underground formulation, and conclude with a preliminary transition formulation which is essentially a combination of the two. The solution strategy of King et al. (2016) are (i) exhaustively searching possible crown and sill pillar placement options using an ad-hoc branch-and-bound strategy and solving the resulting LP relaxations, (ii) using a rounding heuristic to convert the LP relaxation solutions with favorable objective function values into integer solutions, and (iii) using integer solutions to eliminate a number of possible crown and sill pillar placement options to reduce the amount of computation required in (ii).

MacNeil and Dimitrakopoulos (2017) investigated the transition decision at a currently operating open pit mine that exists within the context of a mining complex that is comprised of five producing open pits, four stockpiles and one processing plant. In this paper, the financial viability of a set of candidate transition depths was evaluated to identify the most profitable transition depth. To generate an accurate projection of the yearly cash flows that each candidate transition depth can generate, a yearly life of mine extraction schedule was produced for both the OP and UG components of the mine. A two-stage mathematical programming model (MPM) for production scheduling similar to the work developed by Ramazan and Dimitrakopoulos (2005; 2013) was presented. The proposed method improves upon previous developments related to the OP-UG transition problem by simultaneously incorporating geological uncertainty into the long-term decision-making while providing a transition depth described in three-dimensions that can be implemented and understood by those who operate the mine.

In MacNeil and Dimitrakopoulos (2017) work, a stochastic integer programming formulation used to produce a long-term production schedule for each of the pre-selected candidate transition depths was presented. In addition to a unique transition year, each candidate transition depth corresponds to a unique ultimate open pit limit, crown pillar location and underground orebody domain, all of which are described in the three-dimensional space. An optimization solution outlining a long-term schedule that maximizes NPV is produced separately for the OP and UG operations at each of the candidate transition depths considered.

3.2. Optimization models and algorithms for OP-UG transition interface

Bakhtavar et al. (2009) have reviewed several models and algorithms for determining the transition depth. Bakhtavar et al. (2009) discussed some models and algorithms used in determining the transition depth. The first method for determining transition depth from open-pit to underground was the allowable stripping ratio, which is a relation between the exploitation cost of 1 ton of ore in underground (and in open pit) and the removal cost of waste in relation to 1 ton of ore extracting by open pit (Soderberg and Rausc, 1968; Popov, 1971). In 1982, an algorithm by Nilsson based on cash flow and Net Present Value (NPV) was presented (Nilsson, 1982). However, to consider the transition depth as a critical issue with respect to deposits with combinational extraction, the previous algorithm (1982) was again represented and reviewed (Nilsson, 1992).

In 1992, Camus introduced another algorithm for the transition depth. This algorithm was presented based on the block models and NPV values of blocks for open pit and underground exploitation. The approach basically consists of running the open pit algorithm considering an alternative cost due to underground exploitation (Camus, 1992). In 1997, Nilsson underlined discount rate as the most sensitive parameter in the process of handling the transition depth problem (Nilsson, 1997). In 1998, Whittle programming (4-x) which has been developed to assist in the interfacing of open-pit and underground mining methods was argued and studied. Due to the applied method in the programming, management can make decisions based on quantified operational scenarios of the open pit to underground transition (Tulp, 1998). In 2001 and 2003, an approach with allowable stripping ratio method was developed, and a mathematical form for the objective was introduced. Volumes of ore and waste within the open pit limit were assumed as a function of constant (ultimate open pit) depth (Chen et al., 2001; Chen et al., 2003).

To determine the optimal transition depth from open pit to underground mining, a software based on a heuristic algorithm was prepared by Visser and Ding in 2007 (Visser and Ding, 2007). In the same year Bakhtavar, Shahriar and Oraee introduced a simple heuristic method on the foundation of economical block models with open pit and underground block values. The main process in the algorithm is a comparison between total values of open pit and underground Bakhtavar et al. (2007). A heuristic model was established upon a two-dimensional block model with the values of open pit and underground presented (Bakhtavar et al., 2008).

In 2009, Bakhtavar, Shahriar and Oraee developed their model by modifying Nilsson's algorithm (Bakhtavar et al., 2009). According to Bakhtavar et al. (2009), until 2009, only some of the represented methods can solve but not carefully, problems on researches and studies in this nature. He further added that, the few methods (algorithms) have some disadvantages and deficiencies in finding the transition depth optimally.

The model of Bakhtavar et al. (2009) generates two different optimized mines – open pit mine and underground mine. Each mining method is employed on the same level of mining blocks in series. The NPVs of the optimized mines for each level block are compared and if the NPV of the open pit mine is larger than that of the optimized underground mine, the algorithm transcends by adding the next series of level block to the previously optimized blocks and the NPV of the open pit and underground mines are compared again. The evaluation from the first level to the last level is followed so that a certain level is assigned as an optimal transition depth (level) to establish the crown pillar. The remaining levels below the optimal transition level or crown pillar are emphasized and attended to extract but only utilize the underground stoping method (Bakhtavar et al., 2009). The major problem with this approach is the use of one level as the crown pillar without major consideration to the geotechnical parameters of the intercepting rock formation.

According to Bakhtavar et al. (2012), the most significant problem in the transition problem was the determination of the optimal transition depth from open pit to underground (OP-UG) mining. In 2012, Bakhtavar et al. developed a heuristic model based on block economic values of open pit and underground methods together with the Net Present Value (NPV) attained through mining (Bakhtavar et al., 2012). The NPV of the open pit operation is compared to the NPV of the underground operations for the similar levels. According to Bakhtavar et al. (2012), the model can optimally solve the transition problem based on technical and economic considerations, but did not consider the social effects, requirement of the working force in relation to the open pit mining lifetime, and equipment considerations after open pit mining. Bakhtavar et al. (2012) did not also consider the uncertainties in the geological and geotechnical characteristics of the orebody.

Finch (2012), discussed the important of determining the range of possible transition points within the largest economic pit. Schedules and cash flows developed for each option can be compared to find the best alternative. The main disadvantage highlighted by Finch is that, the effort of generating open pit and underground schedules for all likely transition points at all likely processing rates (and by inference cut-off grades) can be costly and time consuming. This often means that consequently, the problem is not thoroughly explored and therefore the result may be sub-optimal. By applying modern automated optimization software solutions to this problem, the effort can be significantly reduced and the likelihood of developing an optimal result in a palatable time frame at an acceptable cost is dramatically increased (Finch, 2012).

In 2013, Opoku and Musingwini suggested in their studies that, the OP-UG transition should not be based on the transition depth but more appropriately on other dynamic transition indicators (Opoku and Musingwini, 2013). According to Opoku and Musingwini (2013), Musendu (1995) suggested and discussed about the transition indicators as essential for determining the optimum transition level at which a change from OP-UG mining should occur. Opoku and Musingwini (2013) made the transition depth dynamic and reviewed the OP-UG transition decision problem from a stochastic perspective. To capture the dynamic nature of the decision problem, the transition length (T_L) should be T_{Lt}, where t is the point in time at which the parameters are obtained or estimated (Opoku and Musingwini, 2013).

3.2.1. Geomechanics of the crown pillar

A crown pillar is a horizontal part of an orebody between the first stope of an underground mine and the surface of the earth or an open pit or open excavation. A crown pillar is often provided to prevent water entering from the open pit floor into the stope, as well as to reduce surface subsidence and caving. Finding the most suitable crown pillar in a combined mining method using open pit and underground operations, especially block caving, is one of the most interesting and useful problems for mining engineers today (Bakhtavar et al., 2012). The transition from open-pit to underground mining is a complicated geomechanical process.

In the open pit to underground transition, the problems of displacement, deformation and stability of open pit rocks should be properly addressed; otherwise they will directly affect the production, safety and environment of underground mining (Ma et al., 2012). Very large and thick pillars cause the loss of the reserves whilst undersized pillars may cause failure and instability in the mine (Tavakoli, 1994). According to Ma et al. (2012), most of the geometrical and mechanical analyses, analytical analysis, numerical and physical simulations used in the past to study the ground movement and deformation of open pit (Singh and Singh, 1991; Singh and Singh, 1993; Pariseau et al., 1997; Sun et al., 2000; Wang et al., 2000; Bye and Bell, 2001; Liu et al., 2004; Rose and Hungr, 2007; He et al., 2008), lack the long-term monitoring of ground movement and deformation of open-pit after transition from open-pit to underground mining.

The optimization of crown pillar dimension is very important for the metalliferous mining industry. Prediction of optimum thickness of crown pillar is complex, generally based on practical experience with input from numerical analysis and various empirical techniques (Tavakoli, 1994). Numerous parameters affect the stability of a crown pillar (Brady and Brown, 2012). These parameters according to Brady and Brown (2012) are grouped broadly into geological and mining. The geological parameters include the dip of orebody; rock types, hangingwall, footwall and orebody; strength and deformation characteristics of hangingwall, footwall and orebody, as defined by rock mass classification; geometry of multiple ore zones (if applicable); virgin stress conditions and properties of contact zones between ore and country rock while the mining parameters include the geometry of crown pillar and surrounding stopes; support methods (including backfilling); mining sequence and stress redistribution caused by mining.

3.2.2. Placement of crown pillar in OP-UG transition

Crown pillar placement invariably defines the transition interface or zone of the open pit to underground transition problem. Appropriately defining the suitable location of this crown pillar is the beginning to the strategic long-term planning of the mining option optimization, hence, the fundamental burden of most researchers on the mining options optimization problem. According to Bakhtavar et al. (2012), leaving a pillar with adequate thickness will minimize detrimental interference between the open pit and underground mining operations, while maximizing ore recovery. Bakhtavar et al. (2012) assumed that at most one uniform crown pillar with constant height being a multiple of the row (level) height. In their work, the number of required rows to act as the crown pillar was considered with reference to the selected underground stoping method, economic aspects, and geotechnical concerns, and mathematically modelled through two set of constraints.

In their work, MacNeil and Dimitrakopoulos (2017) priori identified the crown pillar envelope for the gold deposit and evaluated four crown pillar locations within this envelope leading to four distinct candidate transition depth. MacNeil and Dimitrakopoulos (2017) further added that, the size of the crown pillar remains the same, although the location changes.

According to King et al. (2016), industry practice places the crown pillar based on: (1) largest economically viable open pit mine, or (2) the extraction method that results in the largest undiscounted profit for each three-dimensional discretization of the orebody and surrounding rock. They determined the sill pillar placement, i.e., locations in which material is left in-situ to allow for a change in mining direction, which adds a layer of complexity. King et al. (2016) used an ad-hoc branch-and-bound strategy to exhaustively search the possible crown and sill pillar placement options before solving the resulting LP relaxations. A rounding heuristic was used to convert the LP relaxation solutions with favorable objective function values into integer solutions. The integer solutions were used to eliminate several possible crown and sill pillar placement options to reduce the amount of computation required in the previous step. Due to the involvement of geology, King et al. (2016), incorporated bound dominance to heavily prune their ad-hoc branch-and-bound tree. They further mentioned that, only 40 of the over 3500 crown and sill pillar placement options have an LP relaxation objective function value greater than the best-known IP objective function value.

The stability of this proposed crown pillar or transition interface is key to strategic decision on the mining options optimization for any potential orebody that could be extracted with either open pit or underground or both mining methods. The placement of the crown pillar or transition interface significantly affects the NPV (Opoku and Musingwini, 2013; Roberts et al., 2013; Ordin and Vasil'ev, 2014; King et al., 2016; MacNeil and Dimitrakopoulos, 2017).

Nowadays, researching methods of influence made by transition from open pit to underground mining are mainly math and physics model research, sliding failure mechanism analogy and engineering analogy. According to Bo-lin et al. (2014), numerical simulation is currently one of the most effective means of studying the stability of the crown pillar. The FLAC software was used by Bo-lin et al. (2014) to study the influence of underground room-and-pillar mining to an open pit slope stability in Changba lead-zinc mine, China by using the equivalent rock parameter identification method to determine the slope rock mass parameters and the safety factor of the slope based on median approximation and strength reduction method.

Wang and Zheng (2010) built up a v-SVR model reflecting the non-linear regularity between underground mining and open slope deformation based on the v-SVR to forecast deformation. Sun et al. (2000) discussed slope rock mass sliding mechanism by analysis method; Nan et al. (2010) used Ansys program to analyze slope stability in Shirengou iron mine and proposed relative safety measures; Shi et al. (2011) used FLAC software to analyze the character of deformation failure about surrounding rocks in complex condition in transition from open-pit to underground mining of Tonglv Mountain NO.1 ore-body. Obviously, numerical simulation is one of the most effective means to analyze slope stability and safety predication (Bo-lin et al., 2014).

3.3. Constraints for OP-UG mining options

According to industry professionals, the production schedule is subject to a variety of technical, physical and economic constraints which enforce the mining extraction sequence, blending requirements, and mining and processing capacities. The transition indicators used; net present value (NPV), stripping ratio, and commodity price, are mostly dynamic over time. Factors that impact the ideal transition from surface to underground operations includes (1) cut-off grades, waste stripping, stockpile generation and stockpile reclamation in surface operations; (2) access to higher grades, dilution, proportion of resource extracted (due sterilization associated with mining method), production costs and capabilities, capital requirement, etc. in underground operations; and (3) tailings capacity, closure cost implications, etc. in combined surface and underground operations. The main constraints applied in the optimization studies of the OP-UG transition have been identified to include the total mining capacity, mining capacity in each ventilation district, total processing capacity, total lateral development capacity, lateral development capacity in each ventilation district, reserve constraints (i.e. to ensure that production activities were completed to a maximum of 100% and did not exceed reserve), and sequencing constraints.

According to Opoku and Musingwini (2013), the transition indicators that Musendu (1995) considered were mining recovery (higher recoveries favor OP over UG), price and grade (higher price and higher grade favor OP over UG), cost (higher OP costs favor UG mining), cost of stripping waste (the higher this cost the earlier the transition), production rate (higher rate favours OP over UG), and underground dilution (does not favor UG as it reduces run-of-mine (ROM) grade. Shinobe (1997) developed a software that enables the mine operator to determine the optimum time of conversion based on discounted cash flow (DCF) techniques and O'Hara and Subo1eski's cost estimation equations. This software assumed that the existence of underground reserves has been confined and that their extraction is technically feasible.

Luxford (1997) highlighted some critical issues to be considered when planning to make the transition. These include cost, workforce recruitment, orebody geometry, production rate, and geomechanics. Hayes (1997) emphasized the importance of economic considerations in OP-UG transition. Hayes indicated that, the following factors affect the decisions on OP-UG: management competence, geological and geotechnical characteristics of the orebody, stripping ratio, and productivity and capital cost of the underground option.

Finch (2012) identified the following as important transition indicators to be considered when making the OP-UG transition decision: feed grade, stripping ratio, commodity price, production rate, and mining cost (open pit and underground mining costs). A set of the constraint considered by Ordin and Vasil'ev (2014) in the optimization studies of the OP-UG transition includes parameters of geotechnologies. These were used to define the depth of transition from open pit to underground mine, mine design capacity, ultimate stripping ratio (the ultimate stripping ratio is only used to find the breakeven point of an open pit mine relative to its depth), and the rate of discounting of expected money flows.

Deterministic approaches fail to account for the uncertain nature of the transition indicators used for the decision-making as well as the geological uncertainties, hence, the failure to address the dynamic nature of the problem (Opoku and Musingwini, 2013). According to Opoku and Musingwini (2013), transition indicators used to inform the OP-UG transition decision are not clearly defined as they vary from company to company, orebody to orebody, and commodity to commodity. However, the commonly used quantitative indicators which address most of the issues identified and applied to gold mines are the margin (as a ratio of gold price to cost) which was chosen to avoid conflicting, views that might arise if price and cost are considered in isolation, average ROM grade, stripping ratio of the open pit mining, NPV of either the open pit alone, underground alone or the combined method; and processed ounces as a proxy for production rate. To account for supplementary and qualitative information on the diversity of issues and differences in ore bodies that must be considered concurrently with the key quantitative transition indicators, Opoku and Musingwini (2013) developed a checklist based on the geology, operational, and geotechnical to guide the transition decision.

3.4. Implementation of models and algorithms for OP-UG mining options

Most of the existing models and algorithms have been implemented and their results assessed. Some of these models have been incorporated into a software. According to Ordin and Vasil'ev (2014), the problem solution to mining options optimizations generally uses the Lerchs–Grossman algorithm, Seymour algorithm, floating cone technique, dynamic programming, neural network, theory of graphs, network flows, etc. Based on these methods, programs of Surpac Vision, NPV Sheduler, Four-X, MineShed, integrated 3D CAD systems of Datamine, Vulcan, MineScape, MineSight, Gemcom and others are widely used (Achireko, 1998; Kaputin, 2004; Kaputin, 2008).

The use of the MIGP formulation for an orebody model usually results in a large scale optimization problem (Askari-Nasab et al., 2011). According to Askari-Nasab et al. (2011), one of the optimization solvers capable in handling such problems is the ILOG CPLEX (2007). This optimizer was developed based on branch and cut algorithm and makes the solving of MIGP models possible for large-scale problems.

To implement their approach in dealing with the transition problem, Opoku and Musingwini (2013) used mining specific software including Datamoine®, Isatis®, Whittle®, XPAC®, and Mineable Reserve Optimizer (MRO®). Isatia software was used to generate the simulated models. MRO was used to determine the mineable stopes for the underground option, and the XPAC was used to schedule the output of the optimization to obtain realistic mining schedule.

In Roberts et al. (2013) work, a standalone open pit is optimized using a combination of the mathematical programming models of the Blasor pit optimization tool and the COMET cut-off grade and schedule optimizer. Blasor uses a mixed integer programming (MIP) formulation to produce an optimized pushback sequence while COMET uses a dynamic programming approach to cut-off and schedule optimization based on a given set of pushback designs. The Blasor output (in the form of an optimum mining sequence) is exported to a software tool called COMET for optimization of the mining schedule. Output from COMET was used to code the optimum open pit schedule into the resource model. For the underground mine, the process of creating mining outlines from the IV0 resource model is conducted using Snowden's Stopesizor software (Myers et al., 2007). Stopesizor modifies a geological block model to identify the optimum mining outline for a range of cut-off values (usually grade based). The mining schedule optimization is conducted using Snowden's Evaluator software package.

In their work, De Carli and de Lemos (2015) used Studio 3 and NPV Scheduler software to assist in the search of the required results in most of the steps of their model in solving the transition problem. King et al. (2016) used the OMP and AMPL/CPLEX solvers in their research.

3.5. Performance evaluation of the models and algorithms for OP-UG mining options

According to Fiscor (2010), the Palabora Mine transited from open pit mine to underground mine in 1996 when the mine announced to proceed with the development of an underground block cave mine with a production rate of 30,000 Mt/day. Fiscor (2010) explains that, Palabora Mining's engineering design work set a precedent for converting from open-pit to underground design. After careful studies, the Palabora Mine transited from open pit to underground mine with a transition zone (crown pillar) of 400 m below the 800 m deep pit. A slope failure occurred at the Northing wall of the open pit after the transition in 2003 (Brummer et al., 2006). Evaluating the performance of models and algorithms are essential to the strength and weakness of such models and algorithms that could lead the way for further studies in the subject area.

In their research, Askari-Nasab et al. (2011) compare the performances of the proposed models based on Net Present Value (NPV) generated, practical mining production constraints, size of the mathematical programming formulations, the number of integer variables required in formulation, and the computational time required for convergence.

Opoku and Musingwini (2013) analyzed the results from their model using normal distributions and their associated and cumulative probability distributions to predict the values of transition indicators at different probability levels. According to Opoku and Musingwini (2013), the transition indicators at a probability of 95% for the four case study mines favored only one mine to transit from OP-UG (combined mining) under the current techno-economic conditions. Opoku and Musingwini (2013) based their analyses on the transition indicators on suggestions from Wright (2012), that, a stripping ratio of 4–17 is considered as a good indicator for the UG option, NPV should be positive and the margin (gold price to cash cost) of 2 is also acceptable since the industry value for 2011 was 1.58.

According to Roberts et al. (2013), to reduce the optimization problem to a manageable size for efficient computation, stope blocks are accumulated into a series of groups or 'bins'. It is assumed that within each group, the contained blocks are to be depleted at the same rate. To produce the best possible approximation of a block by block optimization, each group contains blocks with comparable properties. The blocks are grouped according to ventilation district, IV0 outline, and the year in which the blocks were planned to be extracted by the open pit. In addition to being grouped by ventilation district, blocks are also grouped by their planned open pit extraction year. The extraction year is the governing factor which determines at what time the IV0 value of a block becomes negative.

Ben-Awuah et al. (2016) assessed the performance of their proposed model based on the NPV and smoothness of the generated schedules. The MILP model was setup for open pit and open stope mining to compete for the same material during optimization subject to each method's respective mining and economic parameters. Similarly, Askari-Nasab et al. (2011) assessed the performance of their proposed model based on the NPV, mining production goals and smoothness and practicality of the generated schedules. They tested their model on a Dell Precision T3500 computer at 2.4 GHz, with 3 GB of RAM.

4. Limitations with current models and algorithm for OP-UG mining options

Two key challenges to the mining options optimization problem are the exhaustive consideration of stochasticity of the contributing variables to the models and/or algorithms, and geotechnical considerations in defining the transition interface or zone. Jakubec (2001) and McCracken (2001) stressed on the need to integrate geotechnical models in the strategic long-term mine plans at the prefeasibility stage similar to how geologic models are incorporated. Incorporating geological and financial uncertainties in the mining options optimization models and/or algorithms will result in robust mining projects. Corporate capital budgeting and cost of capital estimation are among the most important decisions made particularly in relation to the impact they may have on the business (Wooldridge et al., 2001). The main challenges of mining variables to the business environment include organizational differences in cost reporting structures, global assumptions, risk appetite and strategic global outlook (Gabryk et al., 2012).

Some of the limitations with current models and algorithms for OP-UG mining options optimization include one or more of the following:

a) optimality assessment,

b) consideration of geotechnics for transition zone,

c) consideration of stochastic variables, and

d) comprehensiveness and efficiency of models.

4.1 Optimality assessment

Optimality assessment of the model is a real challenge to current models and algorithms for OP-UG mining options. The optimality of the problem is therefore compromised with time and cost and the level or gap of optimality is always uncertain. Some of these represented models could solve the transition problems but not carefully, usually giving producing near optimal solutions (Bakhtavar et al., 2012; Finch, 2012). Bakhtavar et al. (2009) noted that, few methods (algorithms) have some disadvantages and deficiencies in finding the transition depth optimally. According to Askari-Nasab et al. (2011), the main disadvantage of heuristic algorithms are that the solution may be far from optimal and in mega mining projects, this is equivalent to huge financial losses. Finch (2012) also highlighted that, the effort of generating open pit and underground schedules for all likely transition points at all likely processing rates (and by inference cut-off grades) can be costly and time consuming, thus, the main disadvantage of current models and algorithms used to solve the transition problem. This main disadvantage implies that, the transition problem is not thoroughly explored and therefore the result may consequently be sub-optimal. By applying modern automated optimization software solutions to this problem, the effort can be significantly reduced and the likelihood of developing an optimal result in a palatable time frame at an acceptable cost is dramatically increased (Finch, 2012).

4.2 Consideration of geotechnics for transition zone

Roberts et al. (2013) acknowledged that, geotechnical constraints were not considered in their work. To verify the impact of geotechnical constraints on the optimal solution, Roberts et al. (2013) recommended that, such constraints need to be incorporated in subsequent studies. The location of the crown pillar, which defines the interface of the open pit to underground transition was priori selected and treated as deterministic. The selection approach to the location of the crown pillar was not known and, according to Opoku and Musingwini (2013), fails to account for uncertainties. MacNeil and Dimitrakopoulos (2017) recommended in their work that, the impact of the size of OP and UG mines on the dimensions of the crown pillar should be investigated.

4.3 Consideration of stochastic variables

Currently, most mine operators schedule the open pit and underground operations independently and then merge the two. However according to King et al. (2016), this approach creates a myopic solution. King et al. (2016) confined the discussions of their approach to open stoping and its associated sequencing options. No stochastic variables like grade and price uncertainty were employed in their model; thus, their model was deterministic. King et al. (2016) further acknowledged that, their methodology in handling the transition problem require additional work to address the accuracy, applicability and optimality gap.

Although MacNeil and Dimitrakopoulos (2017) incorporated grade uncertainty in their work, they further identified some important notable geological uncertainties such as material types, metal and pertinent rock properties and their impact on the strategic long term planning of a mining project. MacNeil and Dimitrakopoulos (2017) further recommended that, future studies should aim to improve on their method by considering more aspects of financial uncertainty such as inflation and mining costs.

4.4 Comprehensiveness and efficiency of models

Shinobe's software based on mathematical programming model (1997) assumed that the existence of underground reserves has been confined and that their extraction is technically feasible. This is a challenge to this model. He later recommended that the results of the program should be viewed only as a preliminary level indication of the economics of underground conversion. No final decision to proceed with the conversion should be taken, solely based on the program's output (Shinobe, 1997). Stacey and Terbrugge (2000) suggested that the transition problem was known but the lack of a model to guide the transition remained an issue. They further noted that the planning and implementation period for transition from OP-UG could take as long as 20 years and so should commence at an early stage.

According to Ordin and Vasil'ev (2014), majority of the existing researches on transition problem lack some constraints and solving of a more general problem – joint optimization of the depth for transition from open pit to underground mining and the design capacities of the open pit and underground mine. Ordin and Vasil'ev (2014) generated curves of NPV and depth of transition from open pit to underground mining for Botuobinskaya pipe deposit. From the generated model, it was interesting to note that comparatively, at the optimum mining depth between 250 m to 400 m, the total NPV of combined open pit and underground mining was higher than the NPV for the open pit mine and the NPV for the underground mine for the same mining depth. In their work, Ben-Awuah et al. (2016) did not consider uncertainty in their model formulation and further recommended that an additional study is undertaken to investigate the mining options including pre-production capital expenditures (CAPEX).

Re-handling, mixing and degradation costs were omitted from the formulation of the model to ensure easy exposition and to enable the use of a special solution strategy. According to King et al. (2016), the re-handling cost proves to be insignificant when incorporated into the transition model. King et al. (2016) observed some fluctuations in both the open pit and underground production, which is undesirable from an operational standpoint, and would require smoothening to create an operationally feasible schedule. However, they added that, these fluctuations are not uncommon in a strategic plan.

In their work, MacNeil and Dimitrakopoulos (2017) incorporated the constraints of mining, processing, metal content and precedence relationships in their model. According to the constraints identified in the works of Opoku and Musingwini (2013) affecting the transition problem, those constraints considered by MacNeil and Dimitrakopoulos (2017) are not exhaustive. Capital investment required to ramp up UG mining was not considered in the application presented for the gold deposit case study (MacNeil and Dimitrakopoulos, 2017).

5. Summary and conclusions

The problem of optimizing reserve exploitation depends largely on the mining option used in the extraction. Some mineral deposits have orebodies that extend from near the surface to several meters in depth. Such deposits can be amenable to both open pit mining and/or underground mining. Current strategic open pit and underground mining interface optimization models have been developed mainly based on determining the transition point or depth between open pit mining and underground mining. An algorithm or model that comprehensively and simultaneously determine an optimized open pit mine, determine the transition interface and further determine an optimized underground mine for any orebody with the potential to be exploited by both surface or underground mining methods or both will add significant value to the mining industry. A matrix showing the various approaches adopted by researchers in tackling the OP-UG transition problem in the last decade has been developed. Challenges and performance evaluation of notable research on mining options strategy have been discussed and opportunities for further research identified. A research approach for further studies on the strategic mining options problem has been outlined.

Notable limitations of existing models and algorithms for the OP-UG mining option have been identified to include one or more of the following: a) optimality assessment of the models and/or algorithms, b) models and/or algorithms did not assess the geotechnical condition of the transition zone, c) consideration of the stochastic variables are not exhaustive, and d) the models and/or algorithms are not comprehensive and efficient.

Although the main sources of uncertainties in mining options study have been found to include financial, technical and geological, research on strategic mining options have handled these uncertainties independently. The incorporation of these geological uncertainties in current strategic mining options have been applied in different forms, including, grade and tonnage uncertainties, probability indices, and the use of algorithms to further define these uncertainties. The incorporation of financial uncertainties together with geological uncertainties are limited in current research on mining option studies. As uncertainties cannot be eliminated in the mining options problem, the best strategy is to quantify uncertainty, reduce this uncertainty as far as investment allows, and finally manage the associated risk during the scheduling procedure.

Over the years, several algorithms (heuristics and meta heuristics) and models (deterministic and stochastic) have been developed to handle the open pit – underground mining options. In the last decade, however, different variations of mathematical programming models have been used by researchers to solve the numerous challenges of the OP-UG mining options problem. The main variations of mathematical programming models are either deterministic (linear programming, integer and mixed-integer programming) or stochastic (dynamic programming, stochastic programming) or combination of both. The authors' conclude by proposing further research into the application of an integrated stochastic mathematical programming model for the mining options optimization problem.

Mathematical programming models are known to be robust and their solutions have a measure of optimality. Some benefits of mathematical programming models include:

a) Robust – mathematical programming models have a well-defined structure that describes the thought process of the modeler in terms of the decision variables (objective functions), and the decision environment (constraints).

b) Objectivity – mathematical programming models are more objective since all assumptions and criteria are clearly specified. Although these models may reflect the experience and biases of the modelers, these biases can be identified by outside observers.

c) Tractability – mathematical programming models allow large and complex problems to be solved in their reduced formed by employing the significant interrelationships among the variables constituting the problem. Thus, they provide a relatively simple and compact approximation of complex decision-making problems.

d) Model solution – mathematical programming models make problems amenable to mathematical and computer solution techniques.

e) Facilitates sensitivity or parametric analysis - mathematical programming models make it relatively easy to find the optimal solution for a specific model and scenario.

f) Optimality measure – mathematical programming models can determine the level of optimality and/or certainty of the solutions to the problem. An optimality gap could be defined to ascertain the optimality level of the solution to the problem.

6. Research opportunities

Quantification of uncertainty and optimization in strategic mine planning plays a significant role in reducing financial risk and environmental footprints, and promoting sustainable development through improved resource governance and total mine reconciliation. The strength of mathematical programming models as opposed to heuristic and metaheuristic techniques will be explored to solve the open pit – underground (OP-UG) mining option problems. Fig. 3 is a schematic representation of the proposed approach to the strategic OP-UG mining options optimization.

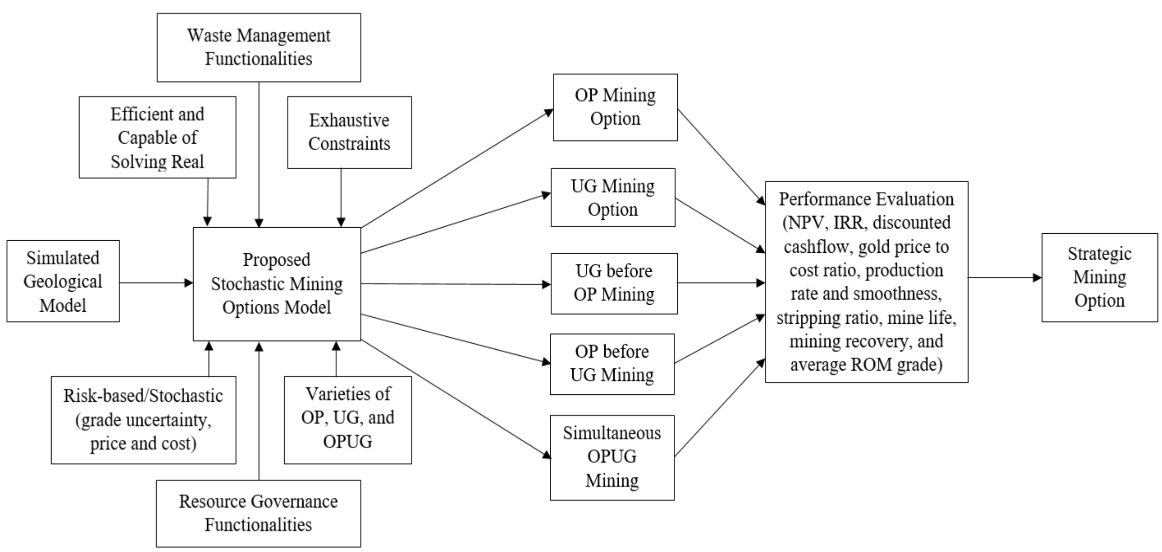

Fig. 3 Schematic representation of the research approach for the strategic OP-UG mining option studies.

Suggested recommendations in addressing the research gap in current models and algorithms will be incorporated in a mathematical programming model with the following characteristics:

a) Robust - when implemented results in:
   i. Separate mining strategy for OP or UG
   ii. Sequential mining strategy for OP to UG or UG to OP
   iii. Simultaneous mining strategy for OP and UG

b) Risk-based/stochastic
   i. Grade uncertainty
   ii. Price and cost

c) Practicality/tractability/generality
   i. Easy to apply
   ii. More varieties of UG and OP mining methods/strategies
   iii. Exhaustive constraints
   iv. Real problem sizes/efficiency
   v. Practical solution run time with known optimality
d) Integrated waste management
   i. Synergy in waste disposal planning
   ii. Improved resource governance and total mine reconciliation

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An Investigation into Dispatch Optimizers using Truck-Shovel Simulation and a New Multi Objective Truck Dispatching Technique

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ABSTRACT

Over the past five decades several models have been developed to make the decision of assigning active trucks to the right shovels. Most of the algorithms try to make decisions that optimize a specific objective and ignore others. This paper introduces a new multi objective truck-dispatching model that assigns trucks based on optimizing multiple objectives at the same time, including the targets and production requirements from the upper stages. Moreover, we have developed a detailed simulation model to test the proposed model against the well-known White and Olson model. We have developed the simulation model in Rockwell Arena and incorporated CPLEX to solve the dispatching models while running the simulation model. However, incorporating complicated decision making tools in the simulation model causes a drastic increase in the simulation run time. Therefore, to deal with the high time consumption, we developed a heuristic dispatching subsystem mimicking the White and Olson model's decisions and compared the key performance indicators and run times for the three techniques.

1. Introduction

Mining projects, and more especially surface mines, are high cost operations that need millions of dollars or in the large mines billions of dollars of capital and operating costs. Material handling procedures, as a main contributor to the operating costs, play a critical role in the mining projects decision making procedure. A large portion of total mining costs in an open pit mine is related to excavating and transporting the material from the mining faces to different destinations outside or within the pit rim. Many researchers believe 50% of operating costs in open pit mines (Alarie and Gamache, 2002) and even in some cases in large open pit mines up to 60% of the operation costs is to be spent on material handling (Alarie and Gamache, 2002; Akbari et al., 2009; Ahangaran et al., 2012; Upadhyay and Askari-Nasab, 2015). Therefore, improving the transportation operation and subsequently decreasing expenses of this subset of the operation by a small percentage will result in significant savings. Two major approaches are usually taken towards decreasing the transportation costs. The first way is to use larger trucks in the truck fleet to transport more material in each cycle. The second way is to reduce the cost of material transportation by implementing operations research techniques to improve productivity of the operation.

In the literature of mining fleet management systems, different efforts have been done since (1964) suggested the use of radio communications between equipment operators and the mine control center. After that, one of the first algorithms to solve truck allocation and dispatching problem in open pit mines was introduced by (1973). In the late 1970s, (1977) introduced dispatching boards installed in the control center using a simplified dispatching technique to manage the operation. Although research continued over 1960s and 1970s, main efforts in the field started from the second half of the 1980s. Since late 1980s researchers focused on developing algorithms based on variety of approaches to optimize fleet management in mines. (Najor and Hagan, 2006; Ercelebi and Bascetin, 2009) developed algorithms based on queuing theory and (White and Olson, 1986; Bonates and Lizotte, 1988; Temeng et al., 1997) developed models based on linear programming.

Developing fleet management systems and evaluating their impacts on the mining operations requires running different operational scenarios in the mines. However, as mentioned above, mining operations and more specifically open pit mining operations are very high cost projects. Therefore, running a single scenario in the real operation for even a short period of time requires spending millions of dollars. Thus, (Sturgul, 1987; Bonates and Lizotte, 1988; Forsman et al., 1993; Kolonja and Mutmansky, 1993; Ataeepour and Baafi, 1999; 2008) implemented simulation modeling to evaluate various dispatching techniques and prove positive impacts of implementing dispatching techniques in mining operations. Most of the simulation studies, from 2010 to 2015, in the field of truck-shovel mining system including (Jaoua et al., 2012; Ta et al., 2013; Dindarloo et al., 2015; Upadhyay and Askari-Nasab, 2015; Chaowasakoo et al., 2017) implemented simulation as a tool to evaluate results of the developed optimization algorithms in their studies without incorporating a new component into their system.

In this paper, the interactions between trucks and shovels in an open pit mining operation is simulated. In the simulated mining operation the model developed in (White and Olson, 1986) has been used for the purpose of optimizing the operation fleet activities. It is worthnoting that the rationale behind using the model developed in (White and Olson, 1986) is its popularity among the mining companies as a proper fleet management system. The model developed in (White and Olson, 1986) is a separate optimizer system that needs to be run in an external optimmization software. Linking this external software to the simulation model increases the simulation model run time. To avoid this increase in simulation run time a simulation based algorithm had been developed to mimic the backbone algorithm of the model developed in (White and Olson, 1986). Then, a multiobjective alogrithm was developed for the so called lower stage (truck assignment) that tries to optimize task of truck dispatching considering three most important objectives of this stage. Afterwards , the simulation model was run for a case study using all three aformentioned optimization algorithms and the results of the simulation were compared.

2. Backbone of Dispatch Optimizer

The model developed in (White and Olson, 1986) takes two steps to dispatch available trucks in an open pit mine. In its first step it tries to optimize production of the operation using two weakly coupled linear programing (LP) models in a predefined time intervals. Afterwards, whenever a truck asks for a new assignment, implementing a dynamic programming (DP) approach, it tries to assign closest truck to the neediest shovel. Solving these three mathematical models, it optimizes mining operations. Vast usage of the the model developed in (White and Olson, 1986) across the world and more specifically over North America for more than 30 years convinced us to implement it in our simulation studies as a benchmark fleet management system. Therefore, we developed a fleet management system based on the backbone algorithm of the model developed in (White and Olson, 1986) in an external optimization software. The optimization model was linked to the simulation model and whenever the simulation reaches the point that requires an operational decision to be made, it calls the optimization model and implements the results of the optimization in the operation. The readers are referred to (White and Olson, 1986) for more information regarding the LP and DP algorithms of the model developed in (White and Olson, 1986) and the way it works to assign trucks to the right shovel.

3. Simulation Based Heuristic

We chose the model developed in (White and Olson, 1986) as a benchmark fleet management system to evaluate goodness of our model. However, calling external optimization software into a running simulation and asking for solutions to the LP models take a lot of time. Thus, runtime problem for the simulation model have forced us to develop a simulation based logic to mimic the model developed in (White and Olson, 1986). This simulation based logic will help the simulation model to not require any linkage to external optimization software. The algorithm follows n-truck-m-shovel approach addressed by (Alarie and Gamache, 2002). In this approach, the shovel's need is updated when it moves to a new polygon and when a truck requests for a new assignment the algorithm runs and allocates the truck to a shovel based on a balance between shortest distance between the shovels and the truck location and the neediest shovel. The simulation based heuristic developed here in this research follows five general steps:

Step 1: Calculating required haulage capacity of shovel *i*.

Step 2: Determining allocated capacity to shovel *i* so far.

Step 3: Finding the shortest paths to the shovels from the current truck position.

Step 4: Calculating the normalized distances of the determined shortest paths.

Step 5: Sending the truck to the shovel with a minimum balance between its need and distance.

4. Multi Objective Model for Truck Dispatching

To deal with the decision making process regarding truck assignment in fleet management system (FMS) a preliminary multi-objective model has been developed in this research which is being presented in this section. The model obtains its required inputs from the current status of the mining operation and using an MILGP approach tries to assign trucks to the shovels.

To introduce the model, the following subsections stand to define indexes, decision variables, parameters, and the calculation procedure to achieve the cost coefficients of the objective function, the MILGP formulation of the model, the governing constraints, and normalization of the goals, respectively.

Index for variables and parameters

i Index for set of Trucks: $i = \{1,...,N\}$;

j Index for set of Shovels: $j = \{1,...,M\}$;

k Index for set of Dumps: $k = \{1,...,D\}$;

t Index for set of weights for individual goals: $t = \{1, 2, 3\}$;

q Index for trucks waiting in queue at shovel: $q = \{1, ..., NTinQS\}$;

Decision variables

x_{ijk} Incoming flow to shovel *j* by assignment of truck *i* to the path of shovel *j* to dump *k*;

x'_{ijk} Outgoing flow from shovel *j* by assignment of truck *i* to the path of shovel *j* to dump *k*;

c^-_{jk} Negative deviation of the met path flow rate for path between shovel *j* and dump *k* compared to desired path flow rate;

c^+_{jk} Positive deviation of the met path flow rate for path between shovel *j* and dump *k* compared to desired path flow rate.

Parameters

S_{ijk} Idle time for shovel *j* if truck *i* is assigned to transport material from shovel *j* to dump *k*;

T_{ijk} Wait time for truck *i* if it is assigned to transport material from shovel *j* to dump *k*;

P_t Normalized weights of individual goals based on priority;

T_i Capacity of truck i;

MF Match factor of the current truck portion of truck fleet available for the assignment and required amount of haulage to meet the production requirements of the operation (it is not well-known match factor introduced by (Burt and Caccetta, 2007));

PC_k Capacity of the plant k: k = {1, ..., O};

SC_j Production capacity of shovel j;

MP_{jk} Path flow rate for the path from source j to the destination k that the production operation has met so far;

PT_{jk} Path flow rate for the path from source j to the destination k;

TR_{ij} Next time truck i reaches shovel j;

SA_{ij} Next time shovel j is available to serve truck i;

TN Current time of the operation;

LD_{ik} The distance truck i must pass to reach the destination k to dump its load;

$ED_{ikj'}$ The distance truck i must pass from the destination k to the next expected shovel j';

$v_{ijk-loaded}$ Average loaded velocity of truck i traveling from shovel j to destination k;

$v_{ij'k-empty}$ Average empty velocity of truck i traveling from dump k to the next expected shovel j';

$Q@D_{ik}$ Queue time for truck i in the queue of the dump k;

D_{ik} Dump time for truck i to dump its material in dump k;

$NTinQS_j$ Number of trucks in queue at shovel j;

$TSpotT_q$ Spotting time for the truck q in the queue;

$TLoadT_q$ Loading time for the truck q in the queue;

Calculations

$$S_{ijk} = TR_{ij} - SA_{ij} \tag{1}$$

$$T_{ijk} = SA_{ij} - TR_{ij} \tag{2}$$

$$TR_{ij} = TNOW + \frac{LD_{ik}}{v_{ijk-loaded}} + Q@D_{ik} + D_{ik} + \frac{ED_{ikj'}}{v_{ij'k-empty}} \tag{3}$$

$$SA_{ij} = TNOW + \sum_{q=1}^{NTinQS_j} \left(TSpotT_q + TLoadT_q\right) \tag{4}$$

Model formulation

The model is formulated considering three operational goals of the operation: 1) minimize the summation of shovel idle times; 2) minimize the summation of truck wait times; and 3) minimize the deviation in the path flow rate compared to the desired flow rate.

The MILGP objectives formulated to optimize the goals are presented in Eq. (5), (6), and (7):

$$G_1 = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{D} S_{ijk} x_{ijk} \tag{5}$$

$$G_2 = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{D} T_{ijk} x_{ijk} \tag{6}$$

$$G_3 = \sum_{j=1}^{M} \sum_{k=1}^{D} \left(c_{jk}^{-} + c_{jk}^{+}\right) \tag{7}$$

Eq. (5) represents total idle time for all the shovels working in the operation. Eq. (6) represents total truck waiting times for all the trucks available for assignment. Eq. (7) represents the difference between flow rate of the paths and the desired flow rates. Applying a non-preemptive goal programming approach the objective function is given by Eq. (8). A challenge here is that the goals are in different dimensions. To have a dimensionless objective function combining all the above mentioned goals it is necessary to normalize the goals. The normalization is done by determining Utopia and Nadir values for each and every goal. The normalized goals are multiplied by the weights to achieve desired priority and the final objective function obtained as Eq. (8).

$$\min Z = P_1G_1 + P_2G_2 + P_3G_3 \tag{8}$$

Constraints

$$\sum_{i=1}^{N}\sum_{k=1}^{D} x'_{ijk} = \sum_{i=1}^{N}\sum_{k=1}^{D} x_{ijk} \qquad \forall\, j \in \{1 \ldots N\} \tag{9}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ijk} = \sum_{i=1}^{N}\sum_{j=1}^{M} x'_{ijk} \qquad \forall\, k \in \{1 \ldots D\} \tag{10}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{D} x_{ijk} \le T_i \qquad \forall\, i \in \{1 \ldots N\} \tag{11}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ijk} \ge MF \times PC_k \qquad \forall\, k \in \{1 \ldots O\} \tag{12}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{D} x_{ijk} \le SC_j \qquad \forall\, j \in \{1 \ldots M\} \tag{13}$$

$$\sum_{i=1}^{N} x_{ijk} + MP_{jk} + c_{jk}^{-} - c_{jk}^{+} = PT_{jk} \qquad \forall\, j \in \{1 \ldots M\}\ \&\ \forall\, k \in \{1 \ldots D\} \tag{14}$$

Constraint (9) assures that incoming trucks to the shovels are equal to the outgoing trucks from the same shovel meaning that whatever truck capacity arrived into a shovel queue will leave that shovel. Constraint (10) makes sure that total incoming haulage capacity into a dump area is equal to the empty trucks' capacity for the trucks leaving that specific dump location. Constraint (11) limits the maximum capability of a truck to incorporate in a transportation task to its capacity. Constraint (12) ensures that material hauled to the processing plants using all the trucks meet the required processing target of each plant. Constraint (13) limits the total haulage capacity sent to a shovel to the shovel's digging rate. Constraint (14) ensures that the path flow rate for each path connecting a source to a destination point is of the desired path flow rate. Moreover, all the variables have a non-negativity constraint.

Normalization of goals

As mentioned before, the goals in the objective function of this study do not match with each other in term of the dimension. Besides, a non-preemptive goal programming approach has been chosen for the optimization of the model. Thus, normalization of the goals before the optimization process is required. In this study, normalizing will be done by the difference of the optimal function values for two so called Utopia and Nadir points. Utopia point sets a lower bound on individual goals in a minimization problem. Nadir point on the other hand, sets an upper bound on the goals in the same types of problems. The results will provide us with the lower and upper bounds of the interval that the objective functions will vary in the Pareto optimal set. Optimizing the system (minimizing) considering only one goal will result in the Utopia point which provides the lower bound of values for individual goals. The upper bounds are derived using the components of a Nadir point presented in (Grodzevich and Romanko, 2006). After normalizing the goals we can solve our multi objective model using an optimization tool.

5. Case study

An iron ore mine located in Iran was chosen as a case study to be used for evaluating the models developed in this research. Mining operation in the case study is being handled by a truck and shovel system. There are three main dumping points for the loaded trucks including two processing plants and one waste dump.

We built a simulation model of the case study. Input parameters are required to run the simulation model. However, these required input parameters are uncertain due to their nature. To account for the uncertainty of the parameters different distributions were fitted on the historical data. Using Kolmogorov-Smirnov and Chi Square tests, the best function was selected for each parameter.

6. Results and Discussions

In order to compare the performance of the dispatching algorithms, we developed a simulation model that incorporates one of the following as the FMS: the model developed in (White and Olson, 1986), the multiobjetive model proposed in this paper, and the heuristic dispatcing technique. The model uses a short-term production schedule obtained from (Upadhyay and Askari-Nasab, 2016) other distribuitions, road network and parameters from the Iron ore mine. Our goal is to compare our model against (White and Olson, 1986) but we developed a simple heuristic mimicing decisions made by (White and Olson, 1986) to avoid run time increases caused by calling the optimization engine in every step of the simulation. The heuristic mimics the model developed in (White and Olson, 1986) to a very good extend with a difference in production of less than 0.9%. At the same time, it runs approximately 650% and 850% faster than a simulation model of the same operation with implementing externally linked FMS in a simple and a complex case, respectively. However, in this paper we only compare our multi-objective model against the original model from (White and Olson, 1986). The simulation model was built in Rockwell Arena and connected to an external optimization software (CPLEX) to solve the models.

After proving that the distributions representing the uncertain input parameters match with the database, the simulation models were set up for 5 replications (decided based on required halfwidths). Then, the model was run for 91 days of operation. Finally, the results of both the simulation models are being presented in Fig. 1 to Fig. 3. Fig. 1 is showing the weekly production of the operation implementing the model developed in (White and Olson, 1986) as the operation FMS. Fig. 2 provides weekly production requirement of the operation implementing the multi-objective model developed here in this reserch. Fig. 3 depicts the histograms of how the queue time at shovels vary implementing each optimization models as the operation’s FMS.

Acording to Fig. 1, the operation moved an average of 950 thousand tonnes of material from the pit per week with a minimum of 903 thousand tonnes and a maximum of 999 thousand tonnes. Beside that, although the total amount of ore produced is following an average of around 250 thousand tonnes, the amount of material sent to each processing plant is varying wildly. In the first four weeks of the operation the FMS tries to send more material to the processing plant 1. This pattern changes by starting the week 5 of the operation by sending more material to the processing plant 2 than processing plant 1 which ends by the end of the week 10 of the operation. This fluctuation is due to the rationle behind the optimization model developed in (White and Olson, 1986).

Fig. 2 represents weekly production of the operation over 12 weeks of the simulation run time implementing the multi-objective model developed here in this research as the FMS. The figure shows that the simulation-optimization model of the operation is removing an average of 1.11 million tonnes of material from the pit on a weekly basis.

It also shows that the amount of ore produced per each week of the operation time is consistent over the run time period. Another major depiction of the graph is that both of the processing plants are fed with the same amount of material with an average difference of only 2.2%.

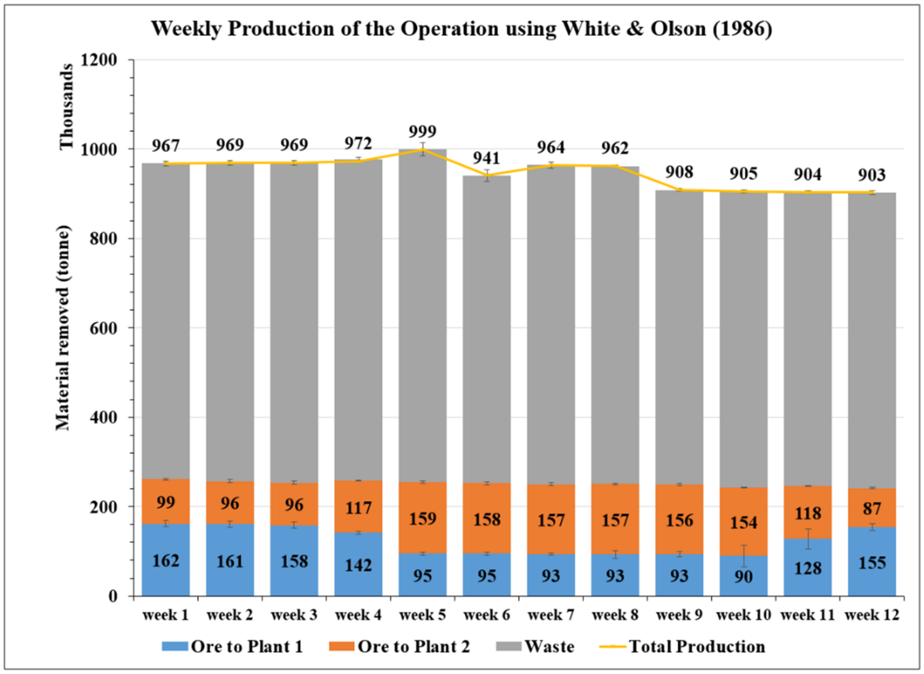

Fig. 1: Total material mined including ore and waste over 12 weeks of the operation implementing the model developed in (White and Olson, 1986).

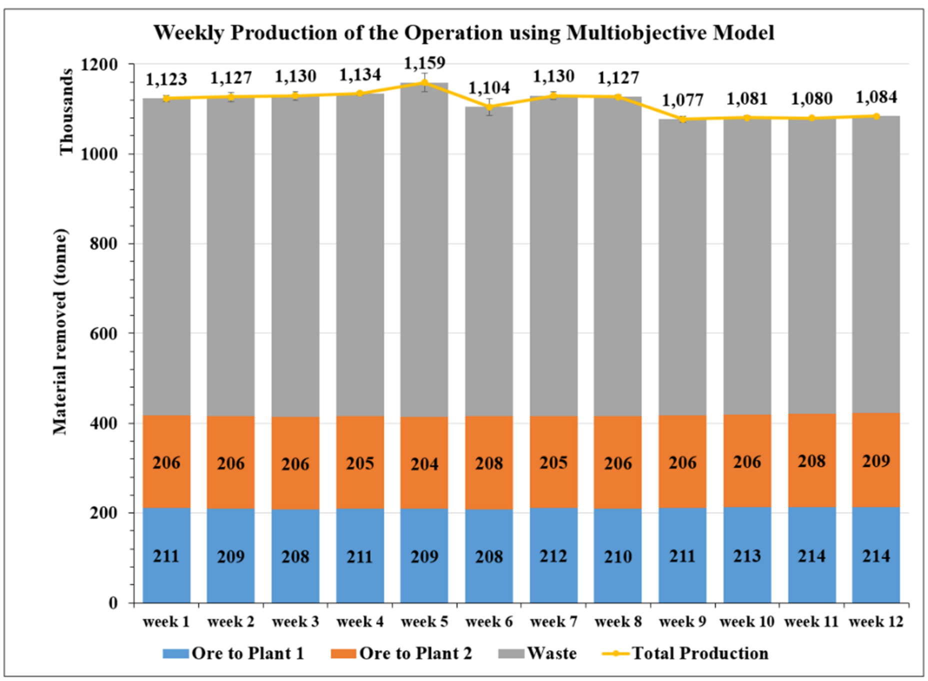

Fig. 2: Total material mined including ore and waste over 12 weeks of the operation implementing the multi objective model developed in this study.

As another important key performance indicator (KPI), queue time at shovel for both FMSs had been investigated and the results are presented in Fig. 3. As it is represented by the graph, using the model developed in (White and Olson, 1986) trucks wait in queue of shovels with a mean of 1.7 minutes which is deviated for about 1 minute. The results are showing slight difference when we implement the multi objective model. Average truck waiting time at shovels while implementing multi objective model is 2.2 minutes with an standard deviation of 1.4 minute.

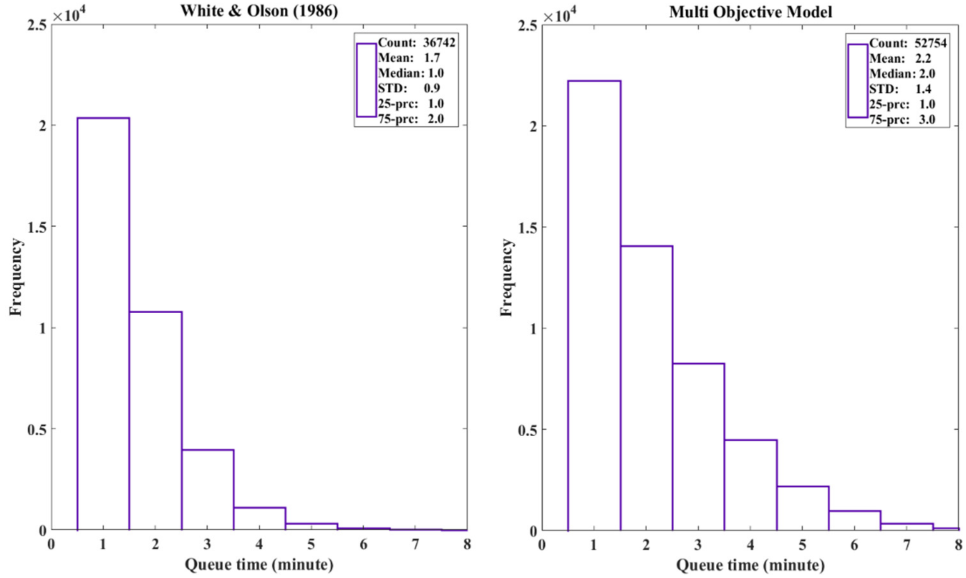

Fig. 3: Histogram of the truck queue time over 12 weeks of the operation (graph in right side represents queue time while implementing optimization model developed in (White and Olson, 1986) while graph in the left side is showing queue time implementing multi objective model developed in this research).

7. Conclusions

In this paper, authors developed two truck dispatching algorithms. The first one is a simulation based heuristic algorithm. This algorithm tries to follow the backbone algorithm of the model developed in (White and Olson, 1986). The second one is a multi-objective mathematical model. This model tries to make decisions of truck assignments in open pit mines based on three major objective of minimizing shovels' idle time, minimizing trucks' wait time, and minimizing deviation from the paths' flow rates. The three aforementioned models were attached to a simulation model of an open pit mining operation. The simulation model was run with the models and some of the results have been presented in this paper.

Comparing the two optimization based FMS, total material removed increases for an average of 8.4% when implementing the multi objective model. The second worth noting conclusion is that, although total weekly ore production of the operation using both fleet management systems are consistent, the plant feed rate for each plant in an operation with multiple processing plants is fluctuating over the production period when implementing the model developed in (White and Olson, 1986). However, this study shows that the multi objective model developed here does not have the feed rate fluctuation problem in a multiple processing operation. The last but not the least conclusion is that truck waiting time at shovels are falling within almost the same range for both of the models with a 30 seconds difference in the average waiting time.

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An economic evaluation of a primary haulage system for a Bauxite mine: load and haul versus in-pit crushing and conveying

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ABSTRACT

The choice of a primary haulage system in mine planning remains a complex problem. Load and haul is normally utilized for material handling in open pit operations. In-pit crushing and conveying (IPCC) is a system that is not typically considered as a primary method of transportation in today's mining world. Using an IPCC system has many advantages including cost savings, safety and environmental impacts. Depending on design parameters, IPCC can achieve full or partial replacement of trucks for material transportation within and out of a mine. The objective of this research is to evaluate the life-of-mine haulage cost by comparing a truck and shovel system with a semi-mobile IPCC system as the primary material handling option. A haulage cost analysis was conducted by comparing the capital, replacement and operational costs of the two haulage systems for a Bauxite mine. In contrast, though operational flexibility is limited with the semi-mobile IPCC system, it reduces the life-of-mine haulage cost by about 60%, which has significant effect on the economic aspect and environmental footprint of the operation.

1. Introduction

It is most common for open pit operations to utilize a shovel and truck fleet as the primary haulage system. An alternate system such as In-Pit Crushing and Conveying (IPCC) is a rather new approach in dealing with the materials handling of a mine. Load and haul systems require the use of many trucks, which can increase the operating cost significantly. Material handling costs generally make up about 40% of the total mining costs. In order to reduce life-of-mine mining costs, an IPCC system can be considered. IPCC can replace the need for a full truck fleet system, or reduce the fleet size. Instead of a cycle consisting of a truck being filled by shovel and either hauling up the pit to a waste dump or to the primary crusher, fixed or semi-fixed conveyors move the material for the majority of the length.

Although there are a few varieties of IPCC systems; the main feature is that a smaller truck fleet is used, where the primary material mover is the conveying system. Shovels are used to load the material while trucks only haul a small distance to the conveyor, where the material is transported further to the respective locations depending on the material type. IPCC systems use conveyors as the primary system to move material while trucks are only used as compliment to the system. The IPCC system of choice is one that will reduce the fleet size as much as possible while being able to work with the pit's geometry and provide some level of haulage flexibility. Based on the recent research work by Dilhuydy et al. (2017), in this study the materials handling system chosen is known as the semi-mobile IPCC system. Semi mobile IPCC uses less trucks and conveyors that work hand in hand to transport ore to the crusher. The trucks are loaded close to the bench and the material transported to the in-pit crusher.

In general, IPCC reduces the reliance on haul trucks, thus reducing total life-of-mine mining costs. Fewer trucks reduce road maintenance cost as primary haulage routes are drastically reduced. On the other hand, capital cost for IPCC systems are higher than load and haul with lower operational costs. With IPCC, a more constant flow of ore is also achievable as the conveying system reduces the amount of downtimes in the cycle of ore transport from the shovel to the mill.

1.1. In-Pit Crushing and Conveying (IPCC) Systems

In-pit crushing and conveying includes three options; Fixed, Semi-Mobile and Fully Mobile. Of the three systems, fixed IPCC systems are typically located near the pit rim, thus away from the mining face. The fixed IPCC system can be moved throughout the mine life however it is beneficial to move the system as few times as possible. As this system still requires fleet of trucks to haul ore to the crusher, with the crusher near the pit rim, the realized reduction in fleet size is smaller in comparison to the other IPCC systems. Semi-mobile IPCC systems are located a short distance from the mining face. This realizes a greater reduction in fleet size. The semi-mobile IPCC system generally moves to a new mining face up to about two times per year or as required to stay close to the mining face. With a smaller fleet size than that of a fixed system, greater operational cost savings are achieved. To achieve the greatest operational cost savings, the fleet size must be minimized to the least amount possible, hence the fully mobile IPCC. Fully mobile IPCC systems require at most a small fleet for minor operational activities including ore re-handle, minor stripping and building berms. This method consists of having a track mounted mobile crusher following each shovel. A mobile conveyor moving independently of the crusher is used to connect the crusher to a fixed conveyor system which transports the ore ex-pit.

In 1956, the first mobile crusher was installed in a limestone quarry in Hover, West Germany (Darling, 2011). The crusher enabled the quarry operator to take advantage of continuous belt conveyor haulage and eliminated a problem of high-cost road construction and maintenance in wet soft ground, with resultant cost savings. Since that time, the number of mobile in-pit crushing and conveying operations has increased to over 1000.

The network of conveyors, spreaders (for waste) or stackers (for ore), crushers and excavators, and sometimes trucks in IPCC are scheduled primarily to optimize productivity and allow for a continuous supply of ore from the mine. Although a few IPCC systems were initially introduced earlier, the last few years have seen an unprecedented level of renewed interest, pushing for greater productivity and continuous mining. Before a mine chooses IPCC as its main haulage system, thorough planning is required. Due to the lack of flexibility compared to load and haul, medium to long-term production planning should be well thought-out and optimized before installation of an IPCC system. The consequences of improper planning are very costly. Despite some of its challenges, there is renewed interest in high capacity production IPCC in base metals.

In comparison to truck haulage system, the operating expenditure of IPCC is significantly less. The capital cost of IPCC installation however, is higher and trade-off studies can be done when factors such as truck tire replacement cost, labor cost, number of trucks required and truck maintenance cost are considered. All these additional cost for the truck haulage system causes a higher operating cost compared to the IPCC system (Dean et al., 2015). Jeric and Hreber (1977) discussed the advantages, disadvantages and operating techniques of the components of the IPCC infrastructure in their study. Koehler (2003) stated that, for a large mining operation with long mine life and long haulage distances, a continuous haulage system such as IPCC are most cost efficient. De Werk et al. (2016) investigated an economic comparison between truck and shovel haulage system and semi-mobile IPCC system for an iron ore deposit. They compared the two systems in terms of material haulage costs and concluded that IPCC systems are more cost effective than truck and shovel system for a mine with long life.

In addition, it is important to note that to transport material via a conveyor system, the largest material to be transported on the conveyor should not exceed approximately one-third of the belt width. Because of this limitation, a crusher is required to reduce mined material into suitable sizes and then conveyed out to the dump or mill. In an IPCC system, both ore and waste material can be crushed and conveyed or only ore material is crushed and conveyed while waste material is hauled using trucks. Dilhuydy et al. (2017) showed with a hypothetical case study that, waste crushing is a feasible less costly alternative for a mine with extended mine life and long haulage distance. In this paper, a cost analysis of a semi-mobile IPCC system for a bauxite ore deposit is evaluated. Based on the results from Dilhuydy et al. (2017), ore and waste material will be crushed and conveyed to their allocated destinations.

1.2. Objectives of the Study

Technological advances in recent years have helped to improve and raise awareness of IPCC systems, but the fact remains that there is a lack of industry interest when it comes to IPCC systems and the tendency is to favor truck and shovel methods of operation for open pit mines. There are many benefits from implementing an IPCC haulage system including cost savings, safety and a significant reduction in the environmental footprint. In order to use an IPCC system, the pit design must be optimized for a conveyor system with straight and elongated walls as large amount of time is needed to set-up and dismantle the system to relocate the conveyors to the next bench. Commonly, the cost of electricity is lesser than the cost of diesel fuel. Since IPCC are electrically powered, they reduced (in the case of fixed and semi-mobile) or completely eliminate (in the case of fully mobile) the use of diesel fuel. This reduction in diesel use reduces the carbon dioxide emissions and the overall carbon footprint of the mine.

In this research, life of mine mining costs is evaluated in terms of selecting truck and shovel or semi-mobile IPCC as the primary material handling system. Capital, replacement and operational costs of each system are evaluated and an economic comparison is conducted to highlights the advantage of the semi-mobile IPCC system over the truck and shovel system. Whittle software (GEOVIA Whittle, 2013) is used to generate the optimum pit shell and production schedule, while GEMS software (GEOVIA Gems, 2016) is used to design the optimum pit shell to meet the required design aspects for implementing the IPCC system.

2. Conceptual Mine Plan

A block model and a topography file were provided to analyze the viability of application of a semi-mobile IPCC system versus load and haul in extracting a Bauxite deposit. A pit optimization was completed and pit designs generated for life-of-mine planning. The pit designs include multiple phases, which allow ore to be extracted selectively throughout the life-of-mine. The three pit phases are designed to fit the use of an IPCC system as an alternative material handling method. An optimum production schedule was generated using Whittle Milawa NPV (GEOVIAWhittle, 2013) algorithm to determine the NPV of the operation and life-of-mine at 10% discount rate. This section discusses the main steps and technical specifications used to complete the pit optimization, pit designs and production schedule.

2.1. Pit Optimization and Design

The pit optimization parameters in Table 1 were extracted from Minkah (2014). The designed pit shell contains 1,566 Mt of ore material with an average grade of 51% Al_2O_3 and 5% SiO_2, and 1,437 Mt of waste material.

Table 1: Pit optimization and design parameters

Parameter	Value
Reference mining cost	$3.16/tonne
Reference processing cost	$9.6/tonne
Selling price	$0.76/%mass
Processing (beneficiation) recovery	80%
Bench height	25m
Bench face angle	75°
Berm width	12m
Overall pit slope	53°

The Whittle shell does not include access, and therefore must be designed to include appropriate ramps. The final pit design is within 8.6% deviation from the Whittle optimized pit shell, which is less than the standard 10% deviation accepted in the industry. Table 2 shows the quantity of material available in the Whittle pit shell and the designed pit limit as well as the segregation of material by pushbacks. From the final pit design, the development of the pit is split into multiple phases in order to suite the semi-mobile IPCC system. Divided into three, the construction of each phase allows for a more controlled independent construction phase, and subsequently a better cash flow and efficient reclamation planning. The three pushbacks are shown in Figure 1. The pushbacks are chosen by splitting the optimum designed pit shell into three areas of similar size. Each pushback has its own ramp access from the North West side of the pit. The pits are mined sequentially to facilitate in-pit waste and tailings dumping, and continuous reclamation.

Table 2: Summary of material tonnages in Whittle pit shell and designed pit phases

Description	Total tonnage (Mt)	Ore tonnage (Mt)
Whittle optimum pit shell	2763	1610
Designed pit shell	3003	1566
Pushback 1	822	402
Pushback 2	1260	587
Pushback 3	921	577

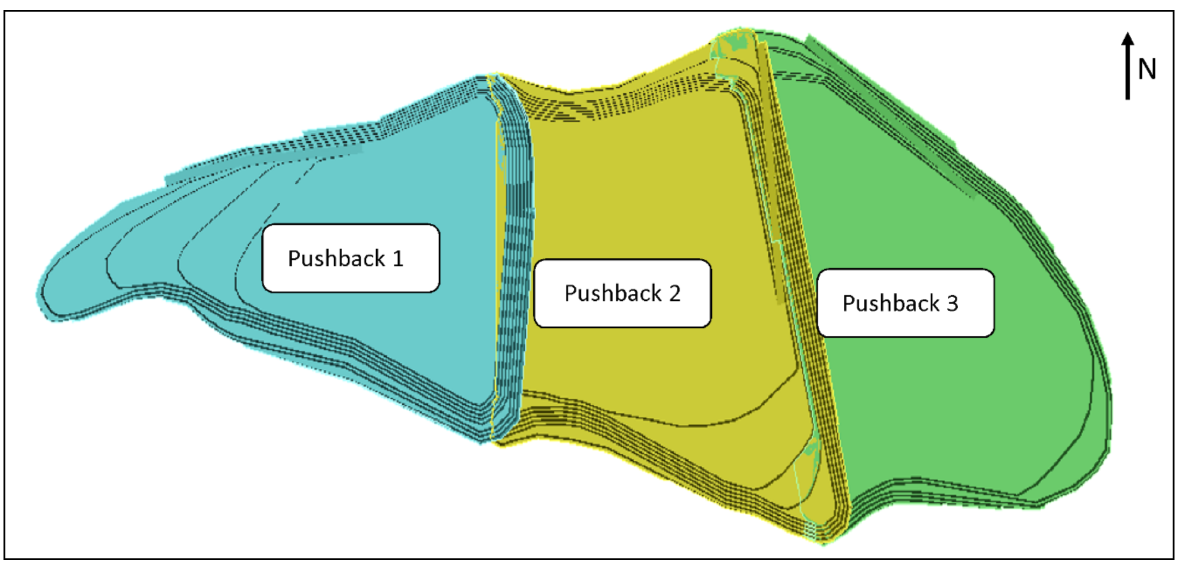

Figure 1: Pushback designs

2.2. Mine Layout

All roads and ramps were designed 40 m wide. All haul roads throughout the mine are two way and allows for clearance for all equipment. Haul road ramps are designed at a constant grade of 10% and will be mainly used for auxiliary equipment as well as haul trucks for the load and haul system.

Waste dumps are essential for open pit operations as waste material must be stripped to expose the ore. The waste material can be used for construction of roads or other facilities. However, a large amount of the waste will not be required and needs to be placed in a waste dump. Dump designs are based on material properties including the angle of repose and particle size distribution related to blasting and ripping. Figure 2 shows the conceptual layout of the mine area including locations for the processing plant, stockpile/reclaimer, waste dump, haul roads and exit points of the ramp system for each pushback.

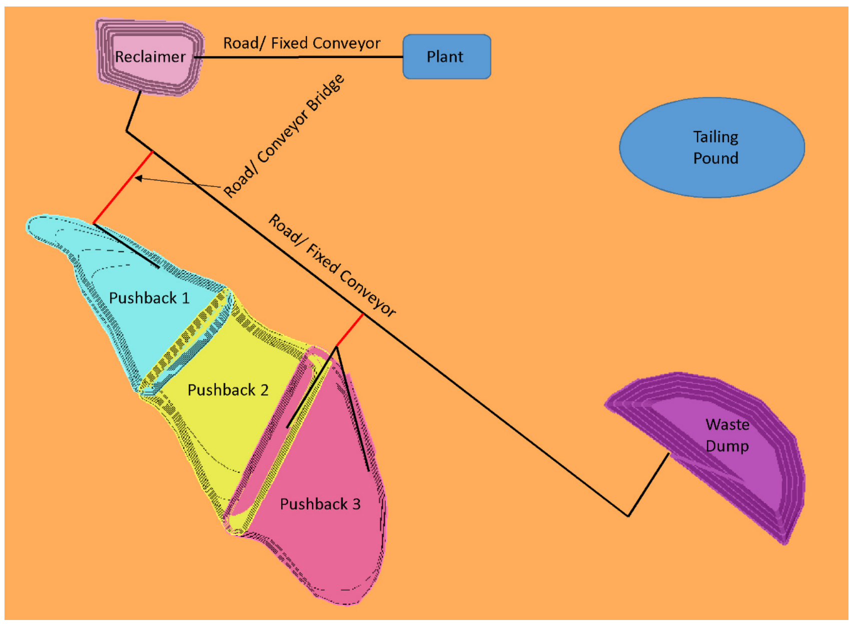

Figure 2: Conceptual layout of the mine area

In the case of using trucks and shovel as the primary haulage system, ore and waste will be hauled out of each pushback to their destinations using trucks while in the case of semi-mobile IPCC, trucks will only be used to transfer ore and waste to the crusher located in the pushback. Conveyors will then be used to transfer the crushed ore and waste to their respective destinations.

Using the phase mining strategy enables each pushback to be mined out completely before moving to the next. An initial ex-pit tailings pond is considered during mining of the first pushback. When pushback one is exhausted, the area could be used as an in-pit tailings pond or waste dump while mining continues in pushback two.

2.3. Production Schedule

Using a stockpile reclaimer system, processing plant capacity was met throughout the mine life. It is envisaged that the stockpile material will be accumulated on a platform and fed with an apron feeder onto an underground conveyor system which transfers the material back into the main processing plant system. The targeted mining capacity was also fully utilized throughout the life of mine. Figure 3 illustrates the mining activity in each pushback including stockpiling. Figure 4 and Figure 5 show the processing plant material tonnage and grade schedule respectively. In each year according to the processing plant capacity and ore availability in the pushback, some amount of ore is reclaimed from the stockpile to the plant. Due to the material reclaiming strategy proposed, the stockpile management is controlled using the First-In First-Out (FIFO) technique.

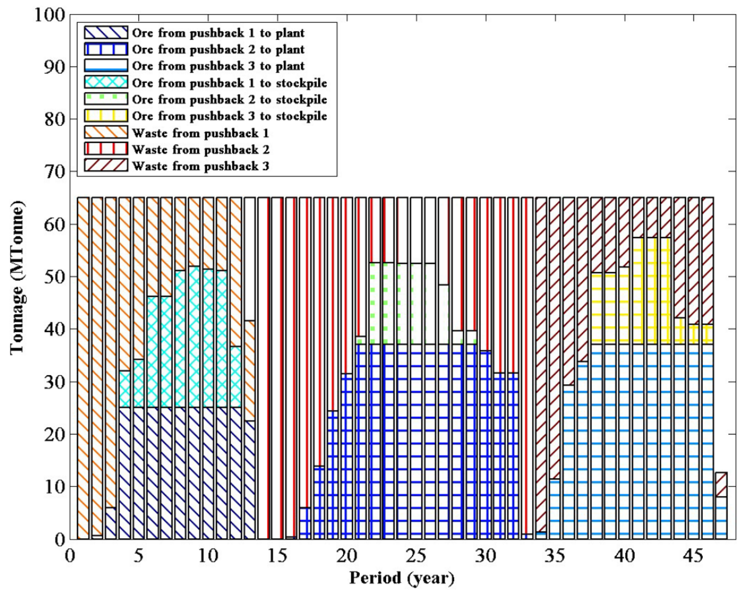

Figure 3: Mining activity in each pushback

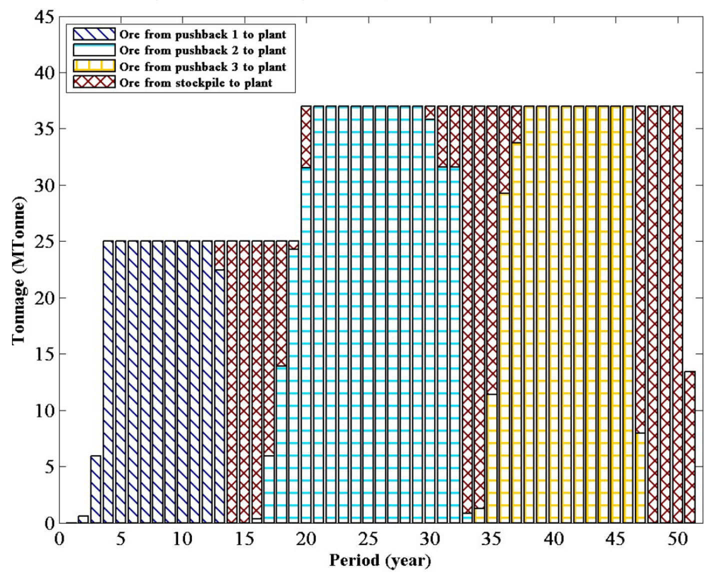

Figure 4: Processing plant material tonnage schedule

Figure 5: Processing plant grade schedule

3. Primary Haulage System

In order to determine the primary haulage system for the case study, two haulage systems were considered: shovel and truck and semi-mobile IPCC. To evaluate the economic viability of each system; the capital costs, replacement costs and operational costs were compared to determine the best haulage system. In the comparison, some costs such as drilling and blasting are assumed to be the same for both systems and hence are not considered.

3.1. Shovel and Truck

Based on the life-of-mine production targets and shovel-truck matching requirements, CAT 6060 FS hydraulic shovel and CAT 793 D truck fleet were selected as part of the primary haulage system. To determine the required hourly production rate, assumptions were made for different mining activities. Table 3 shows the assumptions and calculations for effective working hours for trucks and shovels. Based on the effective working time, the shovel productivity was calculated. Table 4 presents the details for estimating the shovel net production capacity.

Table 3: Effective working hours

Category	Truck	Shovel
Days/Year	360	360
Shift/Day	2	2
Hours/Shift	12	12
Scheduled time per shift (min)	720	720
Total available hours per year	8,640	8,640
Average equipment availability (%)	85	85
Gross machine operating hours per year (GOH)	7,344	7,344
Average equipment GOH per shift	10.2	10.2
Worker usability factor (%)	90	90
Net operating hours per year	6,610	6,610
Coffee break (min)	30	30
Lunch (min)	30	30
Net scheduled (min)	60	60
Shift change (min)	18	18
Inspection and fueling (min)	6	-
Net scheduled productive time (min)	636	642
Job efficiency factor* (post scheduled breaks) (%)	86	86
Time lost to job efficiency (min)	89	90
Net productive operating time/Shift (min)	547	552
Net productive operating hours (NPOH)/Shift	9.1	9.2
Total available productive hours per year	6,552	6,624

Table 4: Shovel and truck capacity estimates

Description	Value
Shovel bucket size	34 (m^3)
Truck capacity	129 (m^3)
Shovel fill factor	90%
In-situ density	2.80 (t/m^3)
Swell factor	30%
Loose density	2.15 (t/m^3)
Tonnes per bucket	65.9 (tonnes)
Time/Pass	0.67 (min)
Passes/Truck	3.31
Rounded	3.00
Loading time (full pass #)	2.00 (min)
Truck leaving time	0.25 (min)
Truck spot time	0.83 (min)
Total time at shovel/Truck	3.08 (min/truck)
Shovel NPOH/Shift	9.1 (hrs.)
Shovel – Truck loads/Shift	177 (loads/shift)
Tonnes per trip	197.7 (tonnes /trip)
Operating shift production capacity	35,075 (tonnes /shift)
Mechanical availability	83%
Utilization	90%
Net shift production capacity	26,201 (tonnes /shift)
Net daily production capacity	52,401 (tonnes /day)
Net yearly production capacity	18,864,511 (tonnes /year)
Shovel life hours	60000 (hrs.)
Truck life hours	55000 (hrs.)

To calculate the total number of trucks required to achieve the mine plan, truck cycle times were determined based on haulage distances and CAT's rimpull charts including 3% rolling resistance. Table 5 shows the estimates for truck speeds and Table 6 presents cycle time calculations for different destinations. The cycle times for CAT 793 D were estimated based on the truck speeds and the calculated distances from pushbacks to dump, and pushbacks to processing plant.

Table 5: Truck speeds (CAT 793 D)

Description	Truck Speeds (m/min)
Flat in-pit (loaded)	333
Flat in-pit (empty)	417
Ramp 10% ascending (loaded)	212
Ramp 10% descending (empty)	333
Topography 2% (loaded)	589
Topography 2% (empty)	667

Table 6: Truck cycle times

Description	Total haulage time (min)
Pushback 1 to plant	17.7
Pushback 2 to plant	27.6
Pushback 3 to plant	28.5
Average travel time to plant	24.6
Pushback 1 to dump	32.2
Pushback 2 to dump	30.8
Pushback 3 to dump	41.5
Average travel time to dumps	34.8
Truck dumping time	1

Based on the average truck cycle time and shovel cycle time, the number of trucks required to meet mine production requirements are calculated. Four shovels and 44 trucks are required to meet the production capacity with operational flexibility. Shovel costs is excluded from the comparison since both systems need the same number of shovels to meet the production requirements. Truck fleet will be replaced approximately every 8 years over the 47 years mine life. The truck operational cost per hour includes tire, lube, diesel and maintenance cost for part and labor. In order to get the yearly operational cost, the total available productive hours per year in Table 4 is used. Table 7 shows the capital, replacement and operational costs for the truck haulage system. Equipment costs were estimated based on CostMine (2016). The US$ to CAD$ exchange rate of 1.2 was considered for the equipment cost.

Table 7: Truck fleet costs (44 CAT 793 D trucks)

Description	Cost (M CAD$)
Capital cost	218
Replacement cost	1,090
Operational cost	5,375
Total cost	6,683

3.2. Semi-Mobile IPCC

In the case of implementing a semi-mobile IPCC system, the shovels are used to extract ore and waste, and the trucks transport these materials to the crusher. Location of the crusher changes during the mine life to reduce haulage distance for the trucks. In this study, an assumption is made that the crusher is initially located at the ramp exit point of the pushback and will be moved downward every two benches equivalent to approximately 3 years. This will keep the average haulage distance for the trucks to a minimum throughout the mine life. Table 8 presents estimated cycle times for each pushback to calculate the number of trucks required to meet the production capacity; 16 trucks are required.

Table 8: Truck cycle times

Description	Average haulage time (min)
Pushback 1 to crusher	6.9
Pushback 2 to crusher	8.8
Pushback 3 to crusher	9.8
Average haulage time to crusher	8.5
Truck dumping time	1

Due to the high mechanization requirement for the semi-mobile IPCC system, the cost of equipment takes up a huge chunk of the capital cost. In the case of the crusher, the cost is a sum of a gyratory crusher and a crawler to give an estimate of the cost of a mobile crusher. Table 9 shows a list of the major semi-mobile IPCC equipment required and their unit capital cost. Table 10 presents the capital, replacement and operational costs of the semi-mobile IPCC system. Equipment costs and their operational costs in Tables 9 and 10 were estimated based on CostMine (2016).

Table 9: Semi-mobile IPCC equipment unit capital cost

Equipment	Quantity	Unit cost (M CAD$)
Crusher	1	23.4
In-pit conveyors	1,500 (m)	9.2
Overland conveyor	7000 (m)	31.8
Spreader (waste)	1	24.3
Stacker/Reclaimer (ore)	2	27.4
CAT 793 D trucks	19	4.9

Table 10: Semi-mobile IPCC costs

Description	Cost (M$)
Capital Cost	237
Replacement Cost	470
Operational Cost	1,954
Total Cost	2,661

3.3. Discussion of Results

As IPCC system is capital intensive, the payback period is usually longer. Thus, the system requires a longer mine life to fully take advantage of it implementation. With 47 years mine life, IPCC will be very beneficial. In this case study, due to long haulage distance, more trucks are required to meet the production capacity. In addition, because of long mine life the replacement cost for large truck fleet is very high. Also, due to the high cost of truck maintenance, the operational cost of IPCC is only 36% of the truck haulage system. Electricity costs are a major factor as the IPPC system reduces drastically the diesel fuel usage which costs relatively higher. Figure 6 shows the comparison between truck and shovel haulage system and semi-mobile IPCC system. From Figure 6, except the capital cost, the IPCC system's costs are lower than that of shovel and truck. By implementing a semi-mobile IPCC system, the overall mining cost can be reduced by $1.33 per tonne compared to the traditional load and haul system.

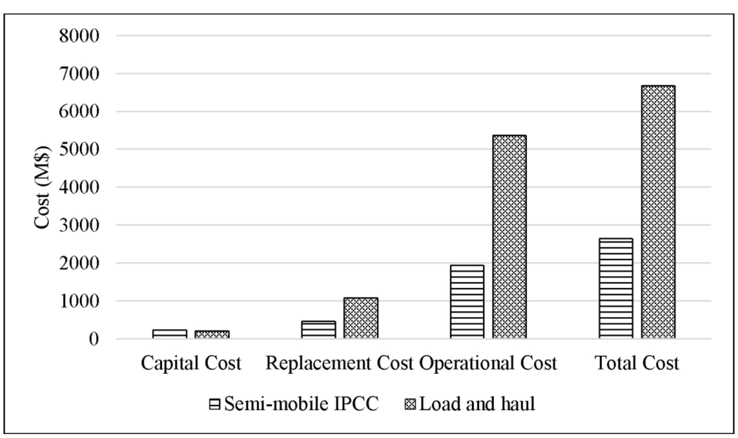

Figure 5: Cost comparison between semi-mobile IPCC and load and haul

4. Conclusion

Technological advances have helped to improve and raise awareness of IPCC systems but the fact remains that there is a lack of industry interest when it comes to IPCC systems and the tendency is to favor truck and shovel methods of operation for open pit mines. There are many benefits from implementing an IPCC haulage system including cost savings, safety and a significant reduction in the environmental footprint. Depending on individual parameters, IPCC can achieve full or partial replacement of trucks for material transport within and out of a mine.

In general, IPCC systems are increasingly cost effective for mining operations that have high capacity with extended mine life, deeper pits, longer haulage distances, high fuel cost and high labor cost. Conveyors in the pit are believed to be the way forward for reduced operational costs in deeper pits with lower grades. Modern conveyor drive techniques like gearless drives can additionally enhance the economic value of IPCC. IPCC should be considered as a main haulage system for open pit mines given appropriate geological and technical parameters. The most important aspect in designing the system is proper and detailed planning as it is less forgiving if the mine planning is poorly done. The more customized the IPCC system implementation is, the less number of trucks are required.

In this study, a semi-mobile IPCC system was evaluated and compared to the traditional load and haul system. Considering only the cost associated with each of the haulage systems, though operational flexibility is limited with the semi-mobile IPCC system, it can potentially reduce the haulage cost of the operation by about 60%. This has significant effect on the economic aspect and environmental footprint of the operation.

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An Improved Approach to Production Planning and Equipment Selection in Oil Sands Operations Through Analysis and Simulation of Hauling Activities

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ABSTRACT

This paper presents improvements on established methods for productivity analysis and forecasting, using data from an oil sands mining operation. Initially, in order to reduce the variance in the productivity performance indicators, efforts were made to conduct extensive dispatch data analysis and classification. With variance in the results comparatively reduced, but still high and its source unidentified, a more detailed study of the truck/shovel activities was warranted. A new framework is introduced: code was developed in order to digitize the mine's road networks and subsequently perform a simulation-based estimation of the haul times from specific sources to dump locations. The concept of EFH (Equivalent Flat Haul) is presented and used as a normalizing parameter that accounts for the effects of gradients and changing road conditions on cycle times. The new approach outlined in this paper provides more accurate estimates for long-range production planning and, in turn, equipment requirements forecasting. The main sources of uncertainty are identified and suggestions on possible improvements to the application of this method at other mine sites are given.

1. Introduction

In the current environment of historically low prices in the mining and oil industries, and with ever-increasing regulation, tax regimes and public scrutiny, profit margins for mining companies have dangerously declined - to the point where the economic viability of individual mining operations and, in some cases, entire companies are jeopardized. Making the operations as lean as possible by cutting operating costs and increasing efficiency in every area while achieving production targets has shifted from something that was, perhaps, a means to marginally increase profitability, to something that is now absolutely critical.

Productivity (and in turn, profit margins) are significantly affected by external factors, but some players in the industry also suffer from a lack of development and focus in the area of operational efficiency. It is estimated that there has been an industry-wide decrease in productivity of approximately 30% in the last decade or so (Lala, et al. 2015).

While Lala et al. (2015) have come up with their own metric and KPIs for McKinsey's mining consulting services, most employees with mining engineering training rely on measured production numbers and equipment utilization parameters, which are constantly recorded in their dispatch system, as their key performance indicators (KPIs). Using a combination of parameters in these two areas, planners are able to estimate the future equipment requirements and/or adjust their plans according to their specific situation. This study uses "TPGOH", as the key performance indicator for productivity, which translates to tonnes per gross operating hour. More specifically, it translates to tonnes of productive material fed to the processing plant per gross operating hours in the truck/shovel equipment combination. A much more thorough analysis of this metric is provided after this introductory chapter.

In order to estimate productivity as well as short and long term equipment needs, and to make changes to the mining plan, the mine planning team at the mine developed a simple algorithm which established a relationship between TPGOH and their production plans. The linking parameter between the production plans and the productivity KPI was the distance of the haul from the source location to the dump location, for every individual record. Estimates were generated by fitting a line to this relationship, which resulted in extremely highly variable results. Historical data for 2 years was used to predict TPGOH ranges for the following year and for LOM (life-of-mine) ranges. This study started by investigating this method and conducting in-depth data analysis to improve the estimates. After reaching a plateau in improvements with this method, it became apparent that the source of uncertainty was coming from the characteristics of the operation itself.

Hauling and transport activities in mining are, in a way, the heart of the operation. The main component in the truck/shovel cycle time is the time spent hauling material from a source to its appropriate destination. Cycle time, in turn is one of the main components in the TPGOH metric, with the other being the tonnage. Since the tonnage is almost always fixed at the maximum payload capacity of the haul truck, the only way to affect the productivity is to make changes to the operation that affect the "GOH" component of the metric. These potential improvements are based in short term ongoing operating costs, replacement equipment selection (medium term) as well long term production planning.

The bulk of the existing research tends to focus on one specific area to optimize, whether in finding efficiencies in long term planning, optimizing short-term schedules, developing new technologies or for larger companies, integrating their operations vertically and use their scale to find added synergies. Conversely, the approach presented in this paper is different, since it yields efficiency opportunities both in the short and long ranges, while focusing on a fairly narrow part of the operation: the hauling of material. For an oil sands mine, hauling is even more critical since the overall geometry of the deposits makes them very extensive in area, resulting in comparatively longer haul routes.

This paper is structured chronologically and coincides with the order in which the work was performed for this study. First, the highly unreliable method employed by the mine staff is reviewed in detail, outlining its shortcomings. Then, the objectives set forth before starting this study are presented, followed by explaining its scope and limitations. Subsequently, a thorough explanation of the initial data analysis performed is presented, followed by the novel approach, which implements the use of Equivalent Flat Haul (EFH), simulation and is the main showcase of this study. Results are then displayed and, lastly some conclusions, insights and plans for future work are defined.

2. Problem Definition

2.1. Old Method

As mentioned in the introduction, the old method employed data from the dispatch system in bulk without much filtering or classification. Figure 1 below shows a sample of the data set that was typically used to predict production at different distances between the sources and destinations for variable horizons (short term to LOM).

While the dispatch data contains several years' worth of production data, only one year is shown. After having retrieved this data, an exponential line of best fit would have been generated. In Figure 1, it can clearly be seen that there is an unreasonable amount of variability, and using a single line of best fit on several hundreds of thousands of data points is an oversimplification of a rather complex system. In addition, estimates were not consistent when varying the years used for the prediction. This motivated the initial stage of data analysis and classification.

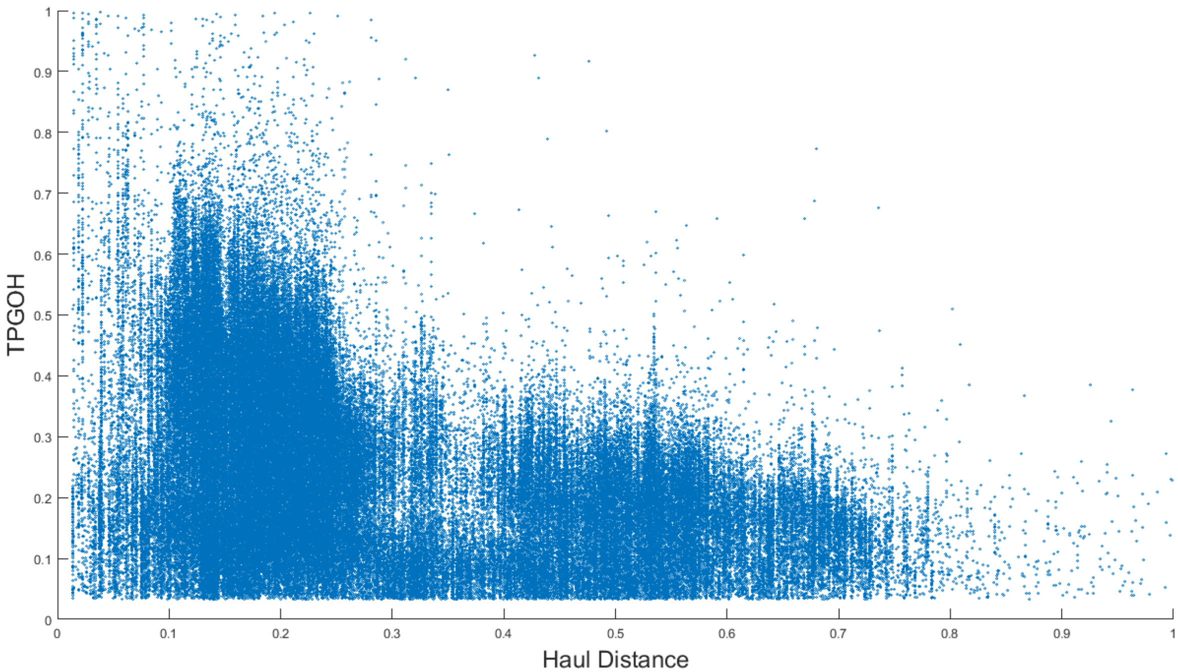

Figure 1. Sample Scatter Plot for Old Method

2.2. Objective

The main objective of this study is to provide planners with a tool, either an improvement of the old method or a new method, that accurately and reliably generates production estimates, so that equipment requirements can be predicted and mining plans can be adjusted accordingly.

In addition, this framework must be able to be used with a modest to reasonable amount of data, be easy to understand, conform to the mine operators' linking method between TPGOH and mine plans via an equipment usage metric (loaded haul distance) and be quick to perform. In addition to providing estimates, it must be able to perform sensitivity analyses and to be flexible, should the characteristics of the operation change. Lastly, the tool should be designed in a way that provides good estimates with basic amounts of data.

2.3. Scope and Limitations

The scope of this study changed since its inception, as it was originally intended to be a data analysis and classification effort, but after identifying the source of unreliability in the estimates, it shifted towards the development of new framework and tools that not only improved on the old method, but replaced it. The framework herein presented, along with the code generated, is applicable not only at this specific mine, but is a useful tool at most other open pit mine sites without much change, especially those that are sensitive to changes in hauling parameters.

There were some pieces of data and information that due to unforeseen reasons were not provided in time for the publication of this paper. This required having to work around some issues that made the overall process of developing this framework longer, but served as valuable lessons from which insights could be shared.

3. Methodology

3.1. Initial Data Analysis and Filtering

The first step in the data analysis effort was to establish realistic caps for the TPGOH metric. These were calculated by looking at cumulative plots which showed where the bulk of the data was, and comparing them to theoretical maximum and minimum values. These were then corroborated with the staff at the mine. Once these caps were in place, most erroneous data, such as zeroes and outliers were removed from further calculations. Subsequently, further data classification took place by filtering the records based on the months indicated in their timestamps, as it was theorized that changes in weather conditions and temperature fluctuations had significant effects on the operations. In addition, the records were classified based on the material type (i.e. ore or waste). These decisions resulted in tangible improvements to the estimates, but took away from the desired simplicity from the staff – effectively shifting from a single line of best fit to several curves. In addition to the previously mentioned filtering by season and material type, the introduction of options in the selection of historical data by year (or years) transformed this into a combinatorial problem. For this specific mine, it was determined that using only the latest (previous) single year of historical production data yielded the best results.

In terms of the key metric, there are 10 individually-recorded fields that go into the calculation of TPGOH, each with their own contribution to the variability of the overall calculation. A breakdown of these fields is given below:

$$TPGOH = \frac{Tonnage}{CycleTime + CycleDelays} \tag{1}$$

Cycle Time is the sum of the following time items:

- Empty Haul
- Queueing
- Spotting
- Waiting to Spot
- Loading
- Full Haul
- Idling at Dump
- Dumping

After conducting analyses for each of these fields, it was found that a disproportionate amount of the total variability in TPGOH came from the haul times – largely from the full haul time component. This was anticipated, since the other time items relate to activities that are fairly short, constant and mechanized in comparison to the travel of haul trucks in the mine's road network. The tonnage field was also quite constant, nor surprisingly, since trucks are almost always loaded to their maximum payload capacity and it matches a predetermined number of shovel passes.

It is important to note that these analyses were performed by grouping records by their loaded haul distance as a controlling parameter. The fact that abundant variability was present in haul times at fixed distance ranges indicated that the hauling activities and road networks needed a more detailed revision.

3.2. EFH

It was hypothesized that the large variability in haul times was due to factors relating in their entirety to the road network and the hauling equipment. More precisely, the problem could be primarily attributed to one or more of the following: truck operator behavior, safety protocols, characteristics and conditions of the road or heterogeneity in the fleet. Burt and Caccetta (2007) provide very detailed insights into the effects of equipment heterogeneity and the match factor on production and cycle times. At this time, it was assumed that the discrepancies were largely due to the gradients on the roads slowing down or speeding up the truck fleet.

Following through with the study and this hypothesis, the next step was to analyze the road network itself. The staff at the mine did not have a digitized version of their road network, but they did provide a very detailed 3-D file of the topography of the entire mine site, acquired by laser techniques. In addition, they provided several files containing instantaneous velocity and location data from their equipment, acquired via GPS trackers every 30 seconds. It was noted that the elevation coordinate in these records was wrong due to measurement error and lack of calibration. In order to work around that, these data points were then overlain on the detailed topography surface, and the network was digitized by hand, joining the relevant points with lines. Once the network had been finished and had the correct planar coordinates, the lines were then “pressed” onto the topographic surface in order to capture the correct elevation and gradient characteristics of the actual roads at the site. This digital representation of the mine’s road network was generated in GEMS, in .dxf format.

In order to try to reduce variability in the calculations, and adhering to the fact that TPGOH was organized by hauling distance, it was necessary to somehow modify the controlling parameter. Equivalent or Effective Flat Haul (EFH) is a parameter that normalizes the distance of a haul by accounting for the changes in elevation in a certain path. EFH, in addition to accounting for the effect of elevation changes on haul times, it provides opportunities to track fuel and energy efficiency in the equipment (Downer EDi et al., 2016). Some companies, such as Newmont, incorporate EFH directly into their key productivity metric by using Tonnes Equivalent Flat Haul per Hour, replacing their previous metric that used kilometres (or simple distance) instead (Newmont, 2014).

This analysis uses a fixed source-destination approach instead of fixed distance intervals, since dispatch systems and availability of equipment make the routes of a single truck and single shift highly variable, and is considered one of the most uncertain aspects of a mining operation (Chaowasakoo et al., 2017).

The way EFH was calculated in this study was by determining a relationship and a factor that would reflect the characteristics of a specific path from a source to a destination. This factor was calculated by performing a simulated estimate of the “actual” travel time of a loaded truck (in this study, CAT 797) using the manufacturer’s rim pull data and the roads’ gradient characteristics, and then dividing it by the time it would take the loaded truck to travel the same distance without any gradients (a flat haul).

The distance from source to destination would then be multiplied by this adjusting factor, giving EFH. Runge Pty. Ltd. outlines this as one of three possible methods of calculating EFH. The other two require capturing velocity data from different scenarios, and calculating average speeds over certain segments, respectively. Campbell and Hagan (2012) present a case study using the former of the two alternative methods, and they conclude that EFH is a useful metric to account for differences in hauling elevation profiles and also serves as a sensitivity analyzer for road design impact on production.

3.3. MATLAB Code

Code was developed in MATLAB in order to conduct these calculations. The program initially reads the information from the road network (in a .dxf input file), and converts all the nodes into usable information. Segments are created based on the node information, therefore generating from-to lines with specific Euclidean distances and coordinates. The gradients are then calculated for each segment. Junctions and intersections are carefully manipulated as they are vital to the logic of the program.

Since the mine's digital road network was generated by pressing polylines into a topographic surface, several thousands of points (nodes), often within centimetres of each other, were created automatically to capture the features of the roads. In order to simplify the calculations, these are merged into segments of user-defined length, and the details of the gradients are captured by calculating a weighted average from the raw data.

This code features an algorithm that finds the shortest path (distance and time) between user-selected sources and destinations (modeled as nodes), returning the total travel distance and extracts detailed route information from the raw data to another matrix. In this matrix, the rim pull value is calculated by multiplying the effective grade (which is the gradient plus the user-defined rolling resistance) by the weight of the loaded truck at maximum capacity. This is done for every segment of road.

Then, the program queries to the manufacturer's rim pull curve in order to obtain the maximum attainable velocity, which varies based on vehicle weight and effective grade. Since the rim pull data is fed to the code on a discrete, table format, the algorithm linearly interpolates between rim pull values to get a more accurate estimate for velocity. The time for every segment is calculated by using its distance and the velocity. The total travel time is a simple addition of the times of every segment in the route. In order to calculate the EFH adjustment factor, the total travel distance is divided by the velocity attainable by a truck on a flat road, only affected by the rolling resistance. This is an accurate representation of the behavior of the trucks at the mines and is a simulation that is similar to that presented by Bonates (1996).

Some other aspects of this particular operation have been included and reflected in the calculations, such as slowing down at intersections and adjusting the time to account for acceleration and deceleration areas. His factor oscillates at over and under one, depending on the characteristics of the haul; over one if the haul is mostly uphill and under one in the contrary scenario. Lastly, the code then generates a box plots showing the variability of the data, using EFH instead of simple haul distance. Figure 2 displays a flow chart explaining the overall framework of the code.

4. Results

A preliminary calculation, performed prior to developing the code, took an average speed on flat hauls from the velocity records and applied an EFH conversion for every record in the database, irrespective of source/destination individuality. This saw a re-arrangement in the data, generating a decreasing trend in TPGOH with increasing EFH distance, which was not present when using the simple haul distance in the old method, as presented in Figures 3 and 4.

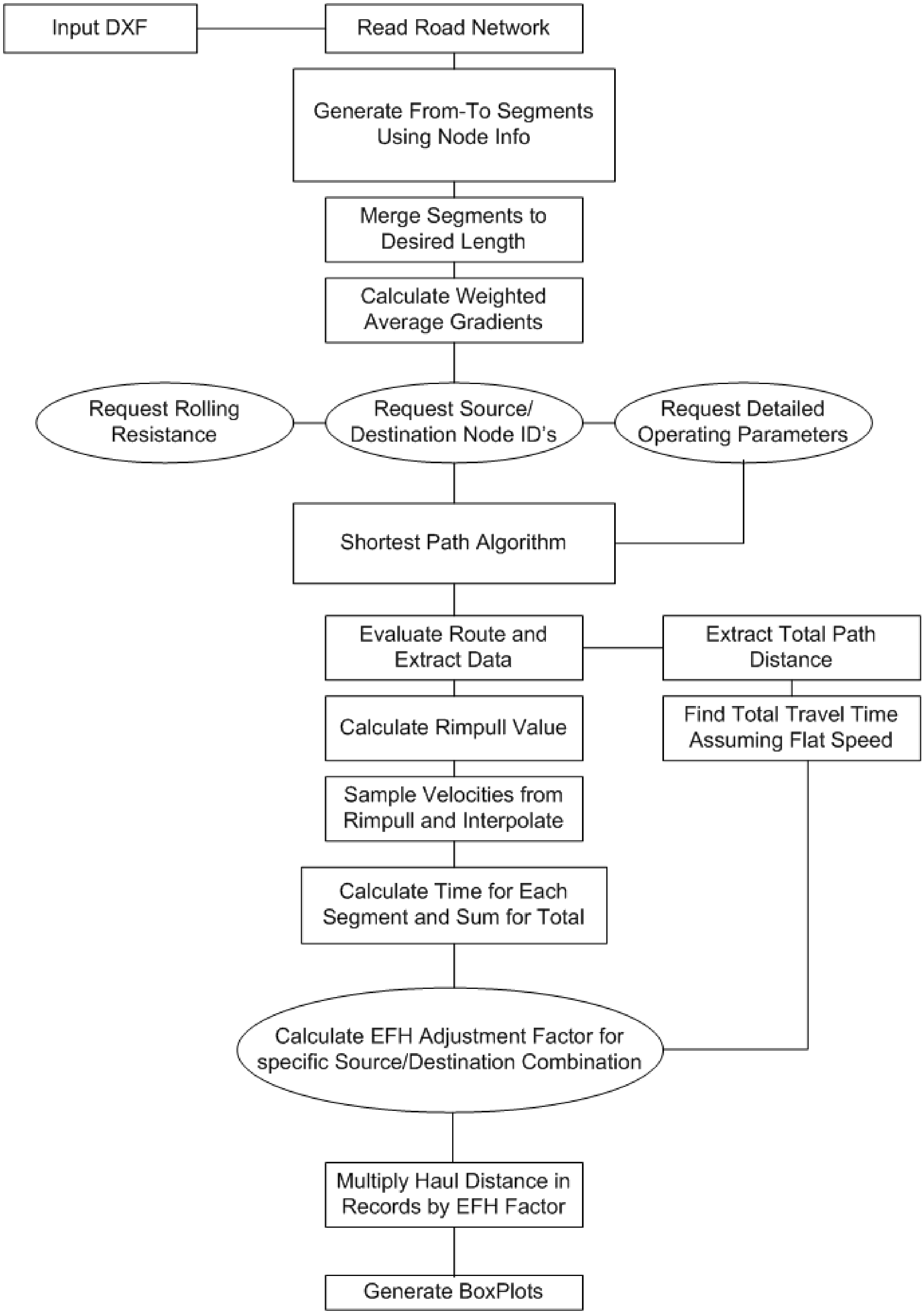

Figure 2: Code Flowchart

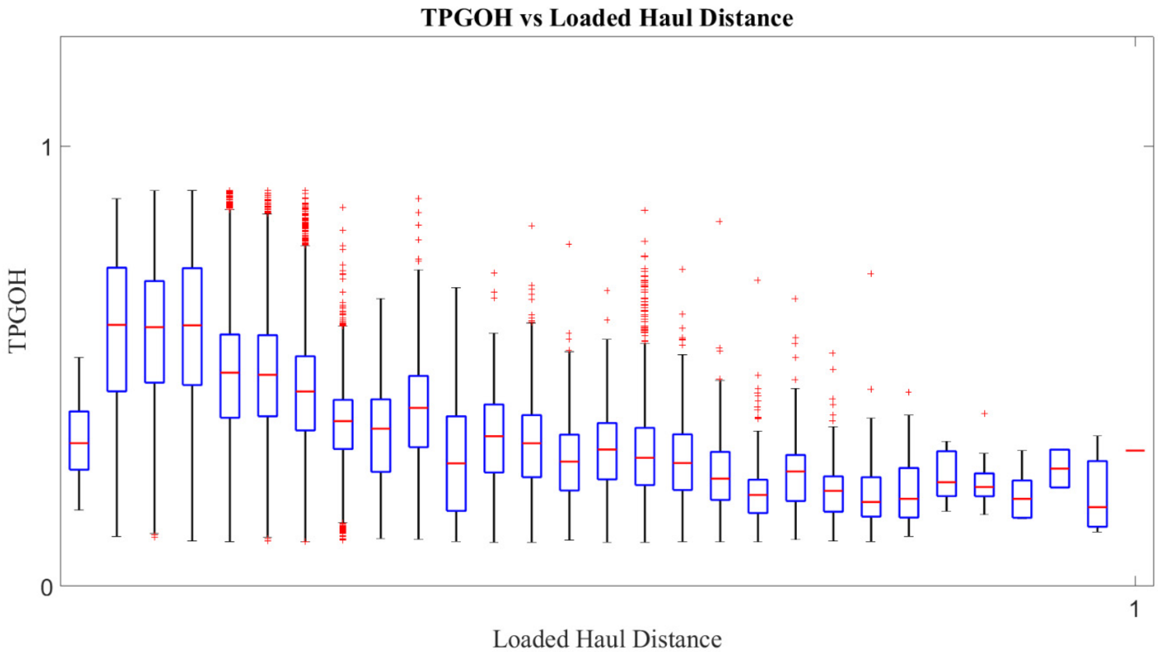

Figure 3: Box Plot Showing Variability of Loaded Haul Distance

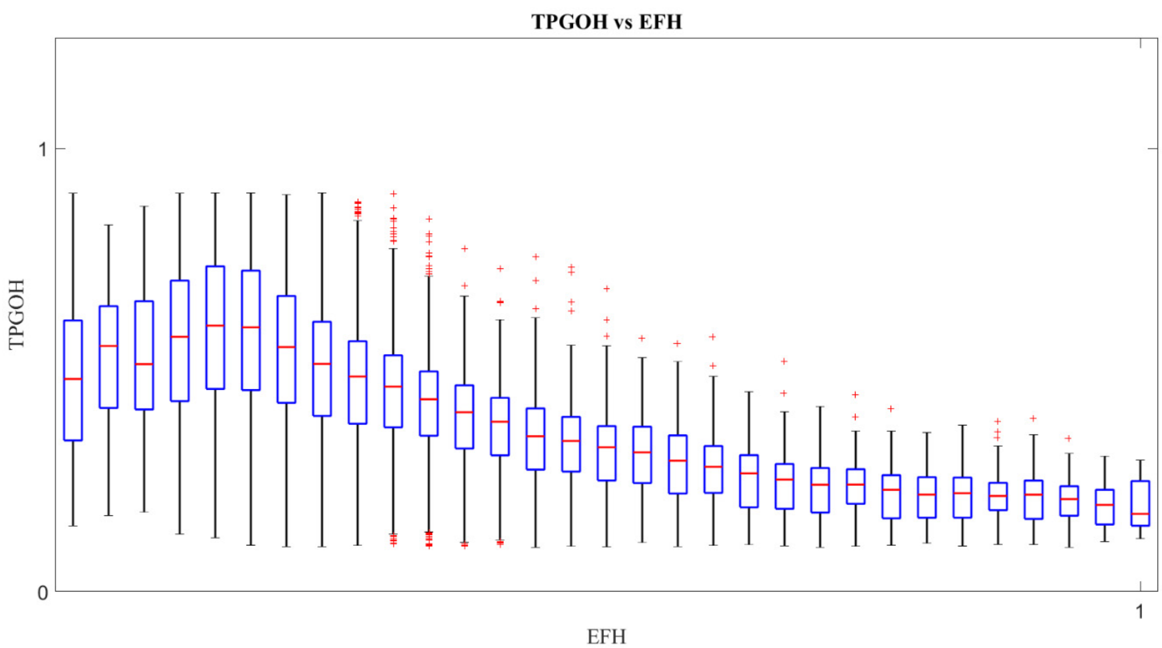

Figure 4: Box Plot Showing Variability of EFH

This gave a preliminary sense that the EFH method rearranges the data in a manner that is logical due to the consideration of gradients and road characteristics on truck performance. The EFH adjustment factor calculated in the code, for a specific source/destination combination, is applied to every historical record in the database (within the same source/destination) and box plots are generated to show a reduction in the variance and display of a downward trend, as shown in figures 5 and 6. An example from a mining polygon source to the processing facility is shown below.

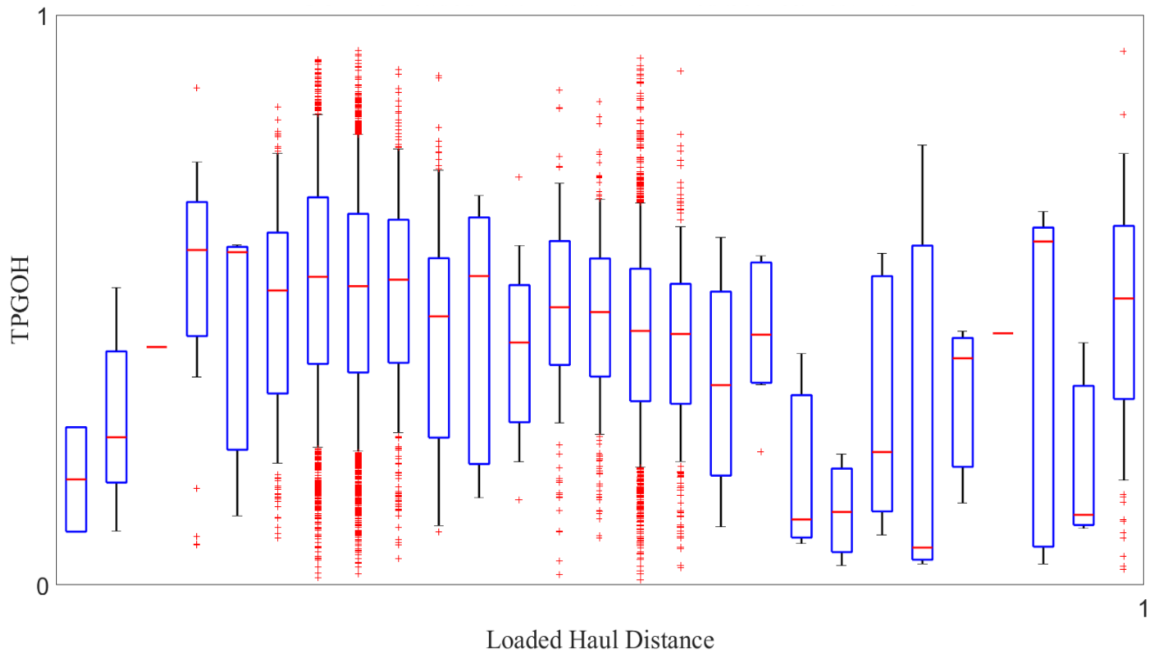

Figure 5: TPGOH vs Loaded Haul Distance for Fixed Source and Destination

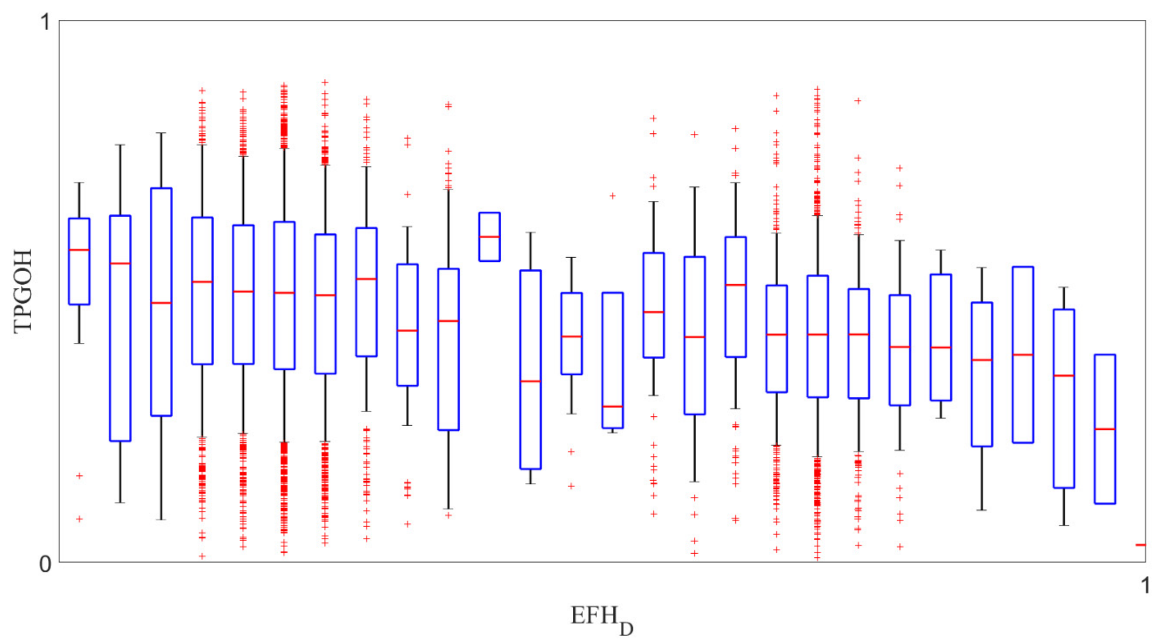

Figure 6: TPGOH vs EFH for Fixed Source and Destination

Even modest improvements to cycle times (in the order of seconds) can add up to very significant changes in equipment utilization per year, especially at large scale operations (Krzyzanowzka, 2007). Variability has been reduced by as much as 20% in some estimates, but is still high, which points to the it not being entirely dependent on the performance of the equipment, but also affected greatly by equipment interactions such as traffic generated by the haul trucks. After consulting with the mine staff, it was revealed that some of the safety rules and regulations imposed on the haul truck operators dictate that speed be reduced drastically in the presence of workers in smaller vehicles and/or on foot.

The effects of these interactions are magnified when considering that mining and development and maintenance of roads happen concurrently, hampering efficiency. In addition, there is variance in distance due to the fact that the size of the mining polygons/faces is quite large, and this prompts the possible introduction of different shortest routes – which cannot be represented in this study without acquiring explicit data provided by the mine staff.

5. Conclusions and Future Work

Throughout the course of this study, the main sources for variability were identified. By developing a tool that accounts for the effects of gradients and road resistance on productivity estimates, the remaining culprit for unreliable calculations is exposed: equipment interaction such as traffic. Further investigation into this area of optimization could be a potential direction for this study. There are, however, many ways to improve on the framework presented in this study. For example, refining the “fine tuning” details of this specific operation and implementing them in the code could yield more accurate results, but requires more data and information.

The next step in this study is replacing the simulation component of the EFH factor by using site-specific velocity records to sample data instead of resorting to rim pull values, which provides the maximum velocity under ideal conditions. This may return more accurate and realistic results. At the time of publishing, the code already has a feature that identifies flat sections of the road, loads velocity records from an external file, fits a distribution and then performs simulation over several realizations to obtain a flat haul velocity value, as opposed to using the manufacturer’s recommended maximum speed. Additionally, performing simulation for every component of the TPGOH metric could lead to more accurate estimates.

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Draw Rate Management in Block Cave Production Scheduling

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ABSTRACT

Planning of caving operations poses complexities in different areas such as safety, ground control, and production scheduling. Draw control is fundamental to the success of block-cave operation. Although some complex theories and mathematical draw control systems have been applied in block-cave mines, most of them did not have an exact production rate curve to manage draw rates of drawpoints and are too complex to provide a solution for real block-caving mines. This paper presents a mixed-integer linear programming (MILP) model to optimize the extraction sequence of drawpoints over multiple time horizons of block cave mines with respect to the draw control systems. Four draw rate strategies are formulated to guarantee practical solutions. Furthermore, dilution and caving are improved indirectly, because the method considers the draw rate strategy. Application and comparison of the four models for production scheduling based on draw control systems are presented using 298 drawpoints over 15 periods.

1. Introduction

Block caving is generally a large-scale production technique applicable to low-grade, massive ore-bodies and the least expensive of all underground mining methods, and can in some cases compete with open-pit mining in cost and production rate. It is a technique which relies on natural processes for its success; therefore gravity is used in conjunction with internal rock stresses to fracture and break the rock mass into pieces that can be handled by miners. This method requires more detailed geotechnical investigations of the ore-body than do other methods in which conventional drilling and blasting are employed as part of the mine production (Rubio, 2006).

Due to an increasing trend in the world to extract minerals and with the mining industry's more marginal resources, it is becoming essential to generate production schedules that will provide optimal operating strategies while meeting practical, technical, and environmental constraints (Burgher and Erickson, 1984; Chanda, 1990; Dagdelen and Johnson, 1986; Pourrahimian, 2013a).

Production scheduling in block caving is generally referred to as draw control. The objectives of draw control are normally separated into short- and long-term scheduling (Diering, 2004a). Draw control in caving operations involves a combination of scheduling and geomechanics (Smith and Rahal, 2001).The use of draw control to mitigate stress damage on the extraction level can be considered as one of the most important aspects of draw management. It is generally accepted that under-draw and over-draw behavior leads to early dilution entry, excessive induced stresses, and loss of planning abilities (Heslop and Laubscher, 1981).

Caveability, in the context of draw control, is primarily concerned with balancing caving rates and production. If draw rates are not controlled, either air gaps or damaging stress concentrations may occur.

This paper, in its entirety, is submitted for publication in International Journal of Mining and Mineral Engineering (IJMME).

Stress is important because undercut advance rates must be maintained to prevent stress damage to the production level. Draw must also be maintained across the production level to ensure that local stress concentrations and premature dilution entry do not occur (Rahal, 2008a).

In general, draw control is fundamental to success or failure of any block cave operations. If draw from the drawpoints is not controlled, many problems and hazards are faced: unbalanced cave subsidence by poor ground control over time, decreased recovery and productivity, premature waste ingress and recompaction of broken material in the draw columns, infrastructure instability, fragmentation size distribution, more dilution, ore handling difficulties that themselves can lead to tunnel and ore pass collapse or haulage systems failure, flow of muck at the drawpoints, and other safety and financial or safety damages to miners are possible to occur. Consequently, a production planning program that does not incorporate the geotechnical properties of the rock mass within the block-cave mining method will not be used for general purposes of production schedules, since such a plan causes many damages. On the other hand, careful control of the production in long-term planning of a block-cave mine will ensure that the schedule of the drawing process within the cave moderates unwanted problems and preserve mining economics associated with production targets.

Production control and implementation of an effective draw strategy once production commences need a strict schedule planning system. The introduction of a draw control system based on mathematical programming that integrates constraints from other disciplines like geology, mining and metallurgy into the system will become more acceptable as real business planning tools. In this paper, a mathematical formulation is developed to optimize the draw rate as a critical parameter of a block-cave operation to maximize economic goals of companies by regarding the geotechnical production rate curves. This paper considers the draw control system as an operational goal with respect to strategic decisions to achieve an exact solution through an operations research technique.

2. Literature review

Several methods are currently used to generate production schedules in block-cave mines. Previous to modern algorithms and computational developments, block-caving scheduling problems, like other underground mining methods in their large size, seemed intractable when formulated in mathematical form, especially in the case of MILP problems. Mining optimization models available in the literature have been developed for block-cave mines, but they solve only a partial type of planning problem. The literature on draw rate models based on the production rate curve (PRC) for block-caving operations is relatively new. Most of the models use simulation in consideration of PRC to evaluate production schedules. There is not a clear example of block-caving production scheduling using a mathematical approach in the literature that formulates draw control system in the block cave according to PRC. Most of the studies consider only upper and lower boundary for draw rate in their modeling. Riddle (1976), Song (1989), Chanda (1990), Guest et al. (2000), Rahal et al. (2003), Rubio and Diering (2004), and Diering (2004a) presented some preliminary mathematical methods in block caving scheduling optimization. Rahal (2008a) described mixed-integer linear goal programming (MILGP) models. This algorithm assumes that the optimal draw strategy is known. Rahal emphasized that the major outcomes from the research were a preliminary optimized life-of-mine production plan and the identification of areas where additional work can refine the parameters used in the optimization. Weintraub et al. (2008) presented a MIP model to maximize the profit of El Teniente, to arrive at good solutions by developing an aggregation scheme based on cluster analysis. They only focused on size reduction methods and they had no reference to issues of draw control rules. Queyranne et al. (2008) presented a MIP model for block caving that maximizes the NPV and uses the capacity constraints of mine production, maximum opened and active drawpoints, and neighbor drawpoints. The model presents a good method for the optimal solution, but it does not consider the geotechnical and other significance constraints. Smoljanovic et al. (2011) presented an MILP model to optimize the NPV value in a panel cave mine to study the drawpoints' opening sequence. The emphasis is in the precedence, geometrical, and production constraints. He did not consider PRC for draw rate constraint. Parkinson (2012) developed three IP models: Basic, Malkin, and 2Cone, for finding the optimal opening sequence in an automated manner.

Parkinson assumed a constant draw rate for the life of the mine. Epstein et al. (2012) presented and solved an MIP model with an objective function of maximizing the NPV that was successfully used in Chilean copper mines by Codelco for both underground and open-pit extraction. Their model uses the drawpoint as the exploitation unit for underground. 'As in Parkinson, the extraction rate of the Epstein method had a constant value in the mine life. Pourrahimian et al. (2012), Pourrahimian (2013b), and Pourrahimian and Askari-Nasab (2014) made other applications of MILP to develop a practical optimization framework for caving production scheduling. They presented a multi-step method for the long-term production scheduling of block caving to overcome the size problem of mathematical programming models and to generate a robust practical near-optimal schedule. Pourrahimian attempted to find an optimal schedule for the life of the entire mine, solving simultaneously for all periods by consideration all required constraints, but he did not consider geotechnical properties of rock mass through the draw rate constraint. Pourrahimian mentioned that the formulation tries to extract material from drawpoints with a draw rate within the acceptable range without considering a specific shape. Alonso-Ayuso et al. (2014) considered a planning MIP medium range problem for the El Teniente mine in Chile to maximize NPV by introducing explicitly the issue of uncertainty. Khodayari and Pourrahimian (2015a) presented a comprehensive review of operations research in block caving. Rubio and Fuentes (2016) described a simulation methodology to compute production schedule reliability. Maximum tonnage that can be drawn from drawpoints based on the overall drawing strategy assumed as optimization function. Khodayari and Pourrahimian (2016) applied MIQP in the long-term scheduling of block cave mines. They used NPV as the objective function. A constant draw rate was one of the applied constraints in the model.

All of these studies have concentrated on determining the optimum configuration of block-caving operation. The main problems associated with the methods presented above can be summarized as follows; some of them did not incorporate, on a routine basis, operational performance to adjust the medium and the long-term plans because of loss of geotechnical rules in the modeling of actual draw management systems. Constraints must be appropriate with the mining method, objective function, and real geotechnical condition of the rock mass. Maximizing tonnage or mining reserves will not necessarily lead to maximum NPV without aggregation reserve and grade constraint to time dynamic behavior of the fundamental models in linking the mine planning parameters and draw rate curves. During the production, the only control is through the drawpoints. Most of the previous research considers a series of simple definitions of the process of moving and drawing of caved material from drawpoints. The researchers have modeled the draw rate constrains regardless of the production rate curves and only by defining lower and upper bounds. Deciding minimum and maximum draw rates of drawpoints is appropriate according to principles of geotechnical rules in all previous studies. However, during the entire life of any drawpoints, draw rate varies.

The extraction from a drawpoint should start with the acceptable minimum draw rate. Then, the extraction increases during the ram-up period until reaching the acceptable maximum draw rate. In the last periods of the life of the drawpoint the extraction rate decreases. A consequence of disregarding the effect of PRC (ramp-up, high production, and ramp-down) on the extraction of a drawpoint is shown in Fig.1.

With defining the upper and lower boundary for draw rate in a mathematical model, although draw rates are in the defined range, they are arbitrary tonnages over the life of drawpoint. This means extraction may start with a higher draw rate (Fig. 1a and 1d) or it can fluctuate (Fig. 1b and 1c) over the life of drawpoint.

In this paper, a mathematical formulation is developed to optimize the draw rate as a critical parameter of a block-cave operation to maximize economic goals of companies by regarding the geotechnical properties of the rock mass. Although following the PRC in mathematical formulation makes the problem more complex and increases the size of the problem, it is a more realistic method. Fig.2 shows a schematic view of a production rate curve. This profile is usually provided by the geotechnical team to consider many factors such as the engineering and geotechnical properties of the rock mass and safety issues in extraction.

For instance, the draw rates established for Cadia East during the cave initiation (up to 30% of the block height) vary from 115 mm/day to 280 mm/day with an average of 190 mm/day. Higher than 30% to the top of the block, the draw rates vary from 280 mm/day to 400 mm/day with an average of 320 mm/day (Flores, 2014).

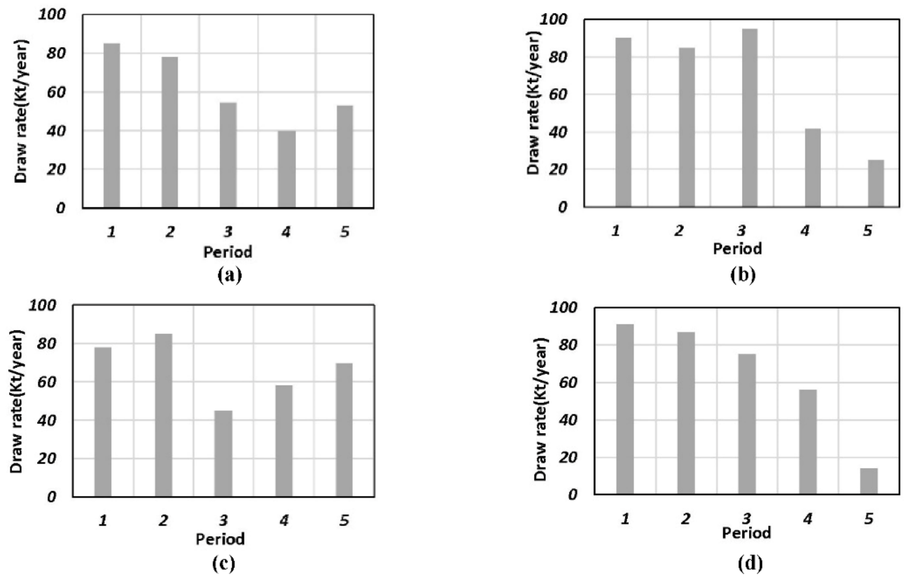


Fig.1. Draw rate variation without considering the production rate curve (min. and max. draw rates are 10 and 100 [kt/year], respectively).

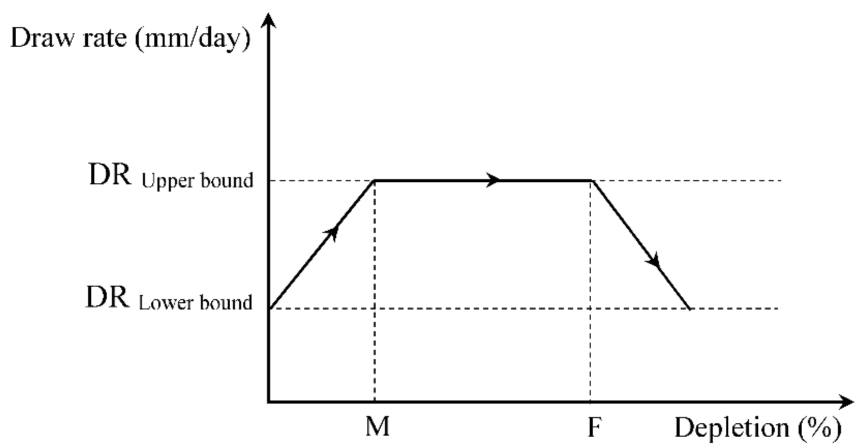


Fig.2. Production rate curve (ramp-up, high-production, ramp-down)

3. Problem Formulation

Mixed-integer linear programming (MILP) formulation presented in this paper maximizes the NPV subject to various operational and geotechnical constraints. These constraints are mining capacity, the maximum number of active drawpoints, the precedence of drawpoints, continuous extraction, the number of new drawpoints, the average grade of production, reserves, activity periods of each drawpoint, and draw rate. Presented draw rate algorithms allow the use of the MILP formulation for large and more complex real block-cave mines planning. The model identifies two types of variables: (i) continuous and (ii) binary. The former is an actual number that represents the percentage of material extraction from the draw column and the later indicates the time when the drawpoint is opened, active, or in any working states during a specified time period. Applications of this variable allows the tractability of "either-or" decisions to the problem. The presented model is coded in MATLAB (2016), and CPLEX/IBM (2015) is used as the optimization engine.

Developing any model requires some decision variables, sets, indices, and parameters that correspond to a scheduling program. The following items are introduced according to the current model:

Indices

$d \in \{1,...,D\}$	Index for drawpoints.
$t \in \{1,...,\mathrm{T}\}$	Index for scheduling periods.
l	Index for a drawpoint belonging to set S^d .

Set

S^d	For each drawpoint, *d*, there is a set S^d defining the predecessor drawpoints that must be started prior to extraction of drawpoint *d*.

Decision variables

$U_{d,t} \in [0,1]$	Continuous decision variable, representing the portion of draw column *d* to be extracted in period *t*.
$A_{d,t} \in \{0,1\}$	Binary decision variable equal to 1 if drawpoint *d* is active in period *t*; otherwise it is 0.
$Z_{d,t} \in \{0,1\}$	Binary decision variable controlling the precedence of extraction of drawpoints. It is equal to 1 if extraction from drawpoint *d* is started in period *t*; otherwise, it is 0.

Parameters

D	Maximum number of drawpoints in the model.
Re_d	Economic value of the draw column associated with drawpoint *d*.
$\mathrm{Re}v_d$	Revenue factor of drawpoint *d*.
DC	Direct mining cost per tonne for drawpoint *d*.
MC	Milling cost per tonne for drawpoint *d*.
OC	Overhead costs.
$DR_{l,d,t}$	Minimum possible draw rate of drawpoint *d* in period *t*.
$DR_{u,d,t}$	Maximum possible draw rate of drawpoint *d* in period *t*.
$N_{Ad,t}$	Maximum allowable number of active drawpoints in period *t*.
$N_{Nl,d,t}$	Lower limit for the number of new drawpoints, the extraction from which can start in period *t*.
$N_{Nu,d,t}$	Upper limit for the number of new drawpoints, the extraction from which can start in period *t*.
Ton_d	Total tonnage of material within the draw column associated with drawpoint *d*.
L	Large number equal to a fraction of $\max\{Ton_d\}$ on minimum draw rate.
i	Discount rate.
M_u	Upper limit of mining capacity in period *t*.
M_l	Lower limit of mining capacity in period *t*.
$Max_{Activity}$	Maximum allowable periods that any drawpoints can be active.
$G_{u,d,t}$	Upper limit of the acceptable average head grade of drawpoint *d* in period *t*.

$G_{l,d,t}$	Lower limit of the acceptable average head grade of drawpoint *d* in period *t*.
$\widetilde{G}_{d,t}$	Average grade of drawpoint *d*.
M	Maximum allowable depletion to reach steady region after ramp-up.
F	Maximum allowable depletion to reach ramp-dawn region after steady.

3.1. Objective function

The objective function of the MILP formulation is to maximize the overall discounted profit, including the cost of the mining operation. The profit from mining a drawpoint depends on the economic value of the draw column and the costs incurred in mining. The revenue per tonne is calculated using the revenue factors per unit of grade material and the mining cost, which includes per tonne overheads and per tonne milling costs (see Equation 1).

$$\mathrm{Re}_d = (\mathrm{Rev}_d \times \widetilde{G}_d) - (DC + MC + OC) \tag{1}$$

The maximization of NPV is closely associated with maximizing ore tonnes, as the ore tonnes generate revenue. The objective function, Equation 2, is composed of the economic value of the draw column and a continuous decision variable $U_{d,t}$ that indicates the portion of a draw column, which is extracted in each period. The most profitable draw columns will be chosen as part of the production to optimize the NPV.

$$Maximize \sum_{d=1}^{D} \sum_{t=1}^{T} \left[\frac{\mathrm{Re}_d}{(1+i)^t} \right] \times U_{d,t} \tag{2}$$

3.2. Constraints

One of the main goals of long-term mine planning would be to integrate internal and external mine planning factors that affect the performance of the mine operation. At the same time, long-term planning is responsible for coordinating strategic goals and operational activities. Obtaining the best solution using an operations research technique forces the mine planner to limit objective function by some constraints, which appear in several different forms: geotechnical, grades, period, advancement direction, and priority of productive units, productivity, production rates, and many others that depend on the mining method.

Knowledge, experiments of mine planners, and corresponding planning horizons have a critical role on the process of assigning constraints to the optimization problems. The following constraints are part of the problem in deriving the formulation:

- **Mining capacity**

$$M_l \le \sum_{d=1}^{D} (Ton_d) \times U_{d,t} \le M_u \tag{3}$$

- **Production grade**

$$\sum_{d=1}^{D} (Ton_d \times (G_{l,d,t} - \widetilde{G}_{d,t}) \times U_{d,t} \le 0 \tag{4}$$

$$\sum_{d=1}^{D} (Ton_d \times (\widetilde{G}_{d,t} - G_{u,d,t}) \times U_{d,t} \le 0 \tag{5}$$

- **Maximum number of active drawpoints**

$$A_{d,t} \le L.U_{d,t} \tag{6}$$

$$U_{d,t} \leq A_{d,t} \tag{7}$$

$$\sum_{d=1}^{D} A_{d,t} \leq N_{Ad,t} \tag{8}$$

- **Precedence of drawpoints**

$$Z_{d,t} - \sum_{j=1}^{t} Z_{l,j} \leq 0 \tag{9}$$

- **Continuous extraction**

$$\sum_{t=1}^{T} Z_{d,t} = 1 \tag{10}$$

$$A_{d,t} - A_{d,(t-1)} \leq Z_{d,t} \tag{11}$$

$$A_{d,1} = Z_{d,1} \tag{12}$$

- **Number of new drawpoints**

$$N_{Nl,d,t} \leq \sum_{d=1}^{D} Z_{d,t} \leq N_{Nu,d,t} \tag{13}$$

$$\sum_{d=1}^{D} Z_{d,1} \leq N_{Ad,1} \tag{14}$$

- **Reserves**

$$\sum_{t=1}^{T} U_{d,t} \leq 1 \tag{15}$$

- **Maximum activity period**

$$\sum_{t=1}^{T} A_{d,t} \leq Max_{Activity} \tag{16}$$

Equation (3) ensures that the total tonnage of material extracted from drawpoints in each period is within the acceptable range that allows flexibility for potential operational variations. The constraint is controlled by the continuous variable $U_{d,t}$. There is one constraint per period. Equations (4) and (5) force the mining system to achieve the desired grade. The average grade of the element of interest has to be within the acceptable range and between certain values.

According to Equations (6), (7), and (8) in each period, the number of active drawpoints must not exceed the allowable number and has to be constrained according to the size of the ore-body, available infrastructure, and equipment availability. A large number of active drawpoints might lead to serious operational problems. According to the determined advancement direction, for each drawpoint *d,* there is a set S^d, which defines the predecessor drawpoints among adjacent drawpoints that must be started before drawpoint *d* is extracted. To control the precedence of extraction, a binary decision variable $Z_{d,t}$, is employed in the Equation (9).

The constraint introduced by Equations (10) and (11) forces the mining system to extract material from drawpoints continuously after opening until closing. Equation (12) is only used for period one. Based on the footprint geometry, the geotechnical behavior of the rock mass, and the existing infrastructure of the mine, the maximum feasible number of new drawpoints to be opened at any given time within the scheduled horizon must be defined on the basis of Equations (13) and (14). Equation (15) ensures that the sum of fractions of the draw column that are extracted over the scheduling periods in maximum value is one, which means there is selective mining, and thereby all the material in the draw column may not be extracted.

The draw rate needs to be fast enough to avoid recompaction and slow enough to avoid air gaps and dilution. The activity period of the drawpoint, in the context of draw control, is mainly concerned with the assessment of draw rates to adjust extraction tonnage of any drawpoint and prevent any recompaction or dilution in activity life of drawpoints. This constraint causes the maximum activity life of any drawpoint to be limited to a deterministic value, so the draw rate of drawpoint must be large enough to maximize the NPV, yet small enough to prevent over dilution. Equation (16) indirectly affects the draw rate by controlling the number of activity periods of any drawpoint. So if the activity period has a large value, then the draw rate can have smaller values, and increasing the drawpoint activity life increases the probability of recompaction and dilution.

3.2.1. Creating Draw Rate Constraints

In the case of caving, the draw control is concerned with extracting ore in such a way as to achieve production targets while minimizing waste entry, as well as preventing the transfer of stress onto mine workings. It is important to ensure that this draw management system is in place before production begins, to prevent resource loss due to production pressures during cave initiation (Preece and Liebenberg, 2007). Production rates are specified as tonnes per square meter per day per drawpoint. This calculation is often linked to a production rate measured in meters per day (or vertical velocity). Selecting the production rate is one of the primary mine design variables required early in the processing capacity evaluation (Charles et al., 2011).

Achieving maximum profit in minimum time periods by increasing the draw volume from drawpoints is the ideal demand of all mining companies. But the geotechnical limitation of the rock mass does not allow mines to draw material with an extreme velocity. Consequently, according to the market assessment and many limitations related to the extraction of mines, companies have different draw strategies to maximize profit, safety and minimize loss of time, financial cost, and fatalities in the mine. The changes in draw rate are normally classified as a drawpoint opening to ramp-up production, steady state production, and ramp-down to drawpoint closure. In this research, the PRC is classified in four alternative general forms to be modeled and practiced by all mines according to their draw requirements. These four forms are as follows: (i) ramp-up, steady, ramp-down (USD), (ii) ramp-up, steady (US), (iii) steady, ramp-down (SD), and (iv) ramp-up, ramp-down (UD).

In the case of mines that geotechnical and economic issues are considered simultaneously, usage of the first model (USD) is proposed. USD is best because the low draw rate in the early years of the life of drawpoints is caused by the geotechnical characteristics of the surrounding environment aligned with the caved material, and in fact, increasing stress caused by draw and caving process relaxes with a relatively soft tendency. Therefore appropriate management of stress relaxation can be done.

Development of an overlap and disjunctive (OD) system for regulating drawpoint production begins by breaking the production profile into a number of regions where each has a binary indicator variable. When the binary variable for each level takes a value of 0, then the draw constraint for that level is relaxed; otherwise, that region binds production.

Each model according to the number of its profile's regions establishes the same number of new sub-constraints. Any of these regions can be available for a draw but their activity returns to a depletion percentage. For example, in the first model (USD, see Fig. 3), there are three regions and it will have three new sub-constraints. The second region is active if the depletion is between M and F, and thus its binary variable ($A_{d,t}$) takes 1 and other regions' binary variables take 0. The OD system determines which of the regions is active. The main goal of draw rate formulation is to find the draw rate of each drawpoint in each period during the optimization of scheduling based on the defined objective function, constraint, and PRC.

In the first step of the proposed OD system, the line equation for each region is written. For this purpose, according to the Fig. 4, the general equation for the ramp-up region is written based on the depletion and the draw rate (see Equation(17)).

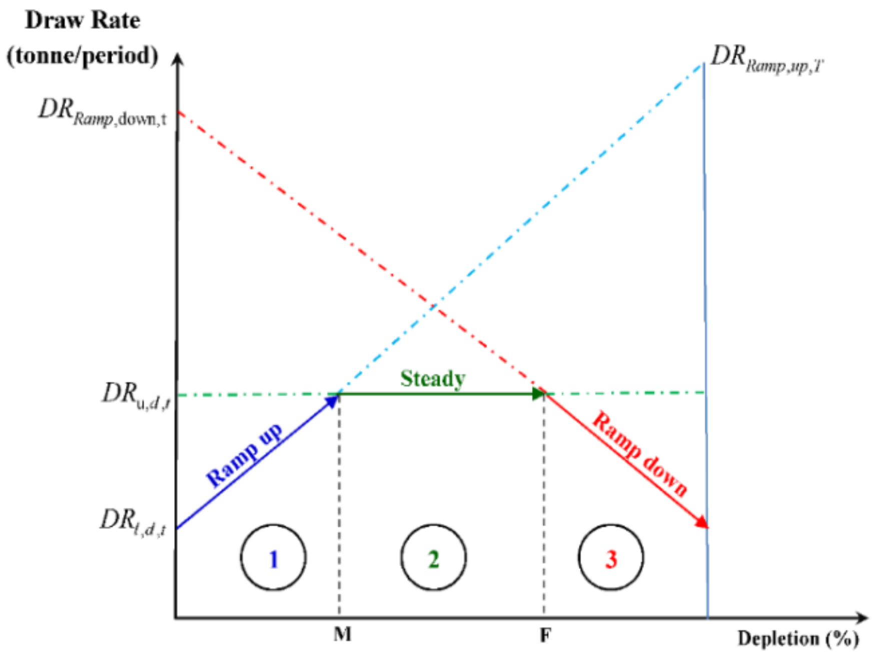


Fig. 3. Ramp-up, steady, and ramp-down situation

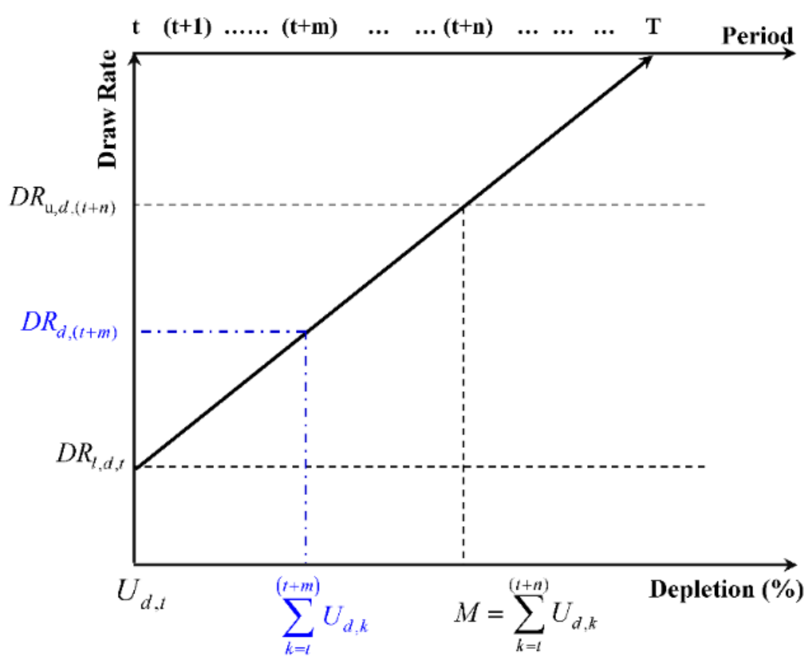


Fig. 4. Basic and ideal line of OD system for ramp-up region

$$(DR_{d,(t+m)} - DR_{l,d,t}) = \frac{(DR_{u,d,t} - DR_{l,d,t})}{M - U_t} \times (U_{d,(t+m)} - U_t) \tag{17}$$

Where M is the maximum allowable depletion to reach $DR_{u,d,t}$; U_t is the percentage of depletion at period 1; $U_{d,(t+m)}$ is the percentage of total depletion until the end of period t. In the simple form, the formula can be written as follows (Equations (18) and (19)):

$$U_{d,(t+m)} = \sum_{t=1}^{t+m} U_{d,t} \tag{18}$$

$$DR_{d,(t+m)} = U_{d,(t+m)} \times Ton_d \tag{19}$$

Equation (20) shows the mathematical structure for the area under the ramp-up region:

$$U_{d,(t+m)} \times Ton_d - \left(\frac{(DR_{Ramp,\text{up},T} - DR_{l,d,t})}{1 - \frac{DR_{l,d,t}}{Ton_d}} \right) \times \sum_{t=1}^{t+m} U_{d,(t+m)} \le DR_{l,d,t} - \left(\frac{(DR_{Ramp,\text{up},T} - DR_{l,d,t})}{1 - \frac{DR_{l,d,t}}{Ton_d}} \right) \times \frac{DR_{l,d,t}}{Ton_d} \tag{20}$$

With a similar process the equations for the steady and ramp-down regions can be written as follows. Equations (21) and (22) are related to the steady and ramp-down regions respectively:

$$U_{Steady,T} \times Ton_d \le DR_{u,d,t} \tag{21}$$

$$U_{d,(t+m)} \times Ton_d + \left(\frac{(DR_{Ramp,down,T} - DR_{l,d,t})}{1 - \frac{DR_{l,d,t}}{Ton_d}} \right) \times \sum_{t=1}^{t+m} U_{d,(t+m)} \le DR_{Ramp,down,T} + \left(\frac{(DR_{Ramp,down,T} - DR_{l,d,t})}{1 - \frac{DR_{l,d,t}}{Ton_d}} \right) \times \frac{DR_{l,d,t}}{Ton_d} \tag{22}$$

Based on the Equations (20), (21) and (22), the problem can be formulated for the required PRC. Fig. 5 illustrates different depletion strategies for a drawpoint.

In the USD situation, extraction begins from drawpoint *d* with a minimum acceptable draw rate in the starting period. Then the draw rate increases gradually (blue) to reach the maximum acceptable draw rate. In the steady region (green), the draw rate follows the maximum acceptable draw rate; therefore the draw rate has a zero slope. By extraction of material from drawpoints and reduction of the amount of remaining materials in the draw columns and reaching to depletion F (%), the draw rate must be reduced with the defined slope. This is the ramp-down region (red). The number of periods in each region depends on M and F values and is obtained as a result of optimization.

Determining M and F is a specific effort and depends on the skill of the geotechnical group of any mines. The number of periods in the steady region decreases by increasing the M value and decreasing the F value. In other words, the USD model is converted to the UD model. A similar definition can be used for other models. However, if the rock mass does not have a good condition, safety problems can happen in the caving progress. If the value of M is too small, it is obvious in the initial periods of extraction with rapid depletion of material that hints of the separation of the huge broken rock from the cave back and, consequently, other phenomena such as air blast and closure of drawpoint are inevitable. On the other hand, if the value of F is too large, rapid rates in the last periods lead to inappropriate control of grade and mixing and reduction in recovery. Therefore, it is clear that the values of M and F have a critical role in the draw control system. Adopting a respectable depletion for these values is crucial to avoid alteration of the models to each other and many undesirable problems.

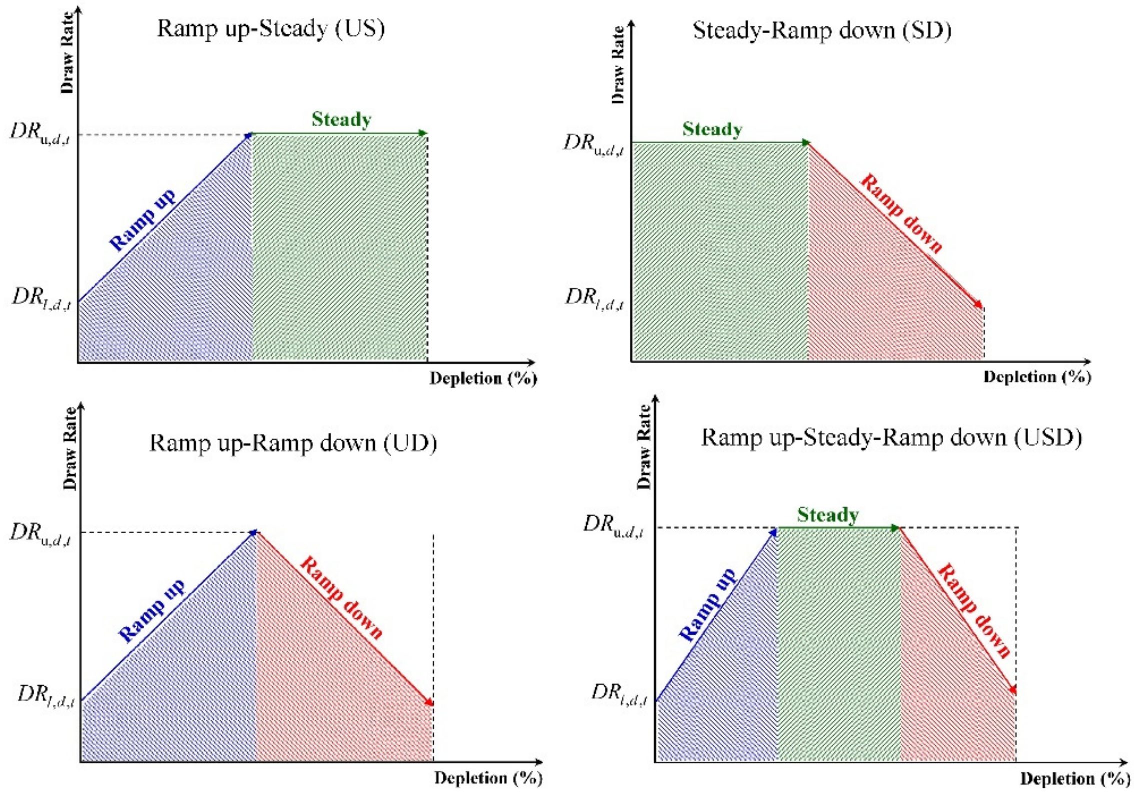


Fig. 5. Different depletion strategies for drawpoint

Finally, in the USD, US, and UD models, in each period that drawpoint depletion is started, the first step of the draw rate must be minimum. Equation (23) forces models to start depletion with a minimum acceptable draw rate.

$$DR_{l,\mathrm{d},t} \times Z_{d,t} - Ton_{d} \times U_{d,t} \leq 0 \tag{23}$$

4. Solving the optimization problem

The proposed MILP model has been developed in MATLAB (2016), and solved in the IBM ILOG CPLEX (2015) environment. A branch-and-cut algorithm is used to solve the MILP model, assuring an optimal solution if the algorithm is run to completion. Authors have used the gap tolerance (EPGAP) of 4% as an optimization termination criterion. This is a relative tolerance between the gap of the best integer objective and the objective of the remained best node.

5. Case study

In this paper, the main dataset contains 298 drawpoints (see Fig. 6b). The total tonnage of material is almost 36.7 Mt with an average density of 2.7 (t/m^3) and an average grade of 1.12% Cu. Fig. 6a illustrates the grade distribution. The performance of the proposed MILP models is analyzed based on the maximizing net present value at a discount rate of 12%. The draw control system, by enrolling an exact production rate curve, seeks to optimize and present a practical block cave planning. This model assures that all the constraints are satisfied during the mine-life.

The models were tested on a Dell Precision T7600 computer with Intel(R) Xeon(R) at 2.3 GHz, with 32 GB of RAM. In all models, as part of the implementation of the models, the maximum depletion of the draw column from the ramp-up to steady (M) is assumed to be 42%, the maximum depletion of draw column from steady to ramp-down region is assumed to be 90%. The scheduling parameters have been summarized in Table 1.

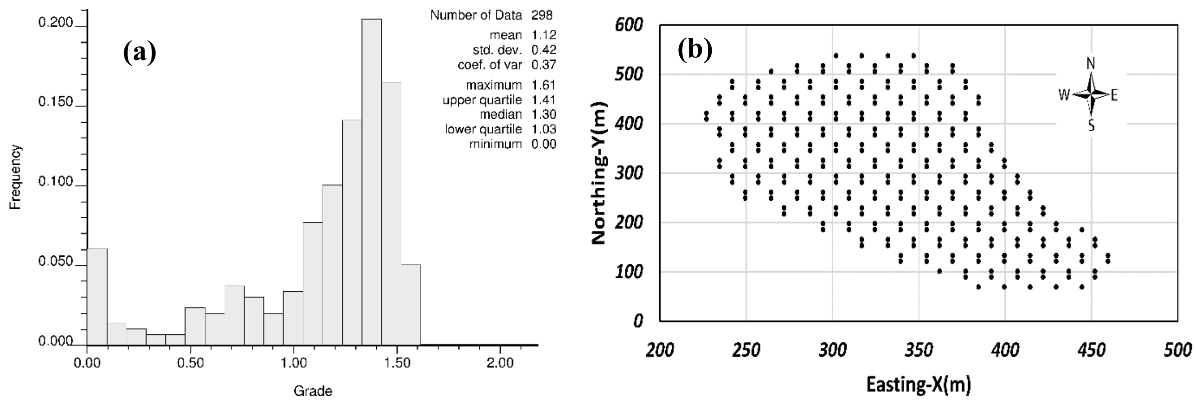


Fig. 6. Case study: (a) grade distribution of %Cu, (b) drawpoints' configuration (dots represent drawpoints)

Table 1. Production scheduling parameters

Parameters	Value	
Number of periods	15	
Maximum number of activity period of drawpoints	5	
Draw rate (kt/year)	Min	11
	Max	40
	M (%)	42
	F (%)	90
Number of active drawpoints	Period one	100
	Other periods	75
Number of new drawpoints	Max	35
	Min	5
Grade (%)	Max	1.5
	Min	1.0

The models are verified over 15 periods in the south to north (SN) advancement directions. This advancement direction was selected using the methodology presented by Khodayari and Pourrahimian (2015b).Khodayari and Pourrahimian (2015b) showed that the cumulative economic value of all drawpoints can be used to determine the best advancement direction to maximize the NPV. Fig. 7 shows the mining advancement direction for 298 drawpoints. As shown, the best direction is from south to north (SN).

The problem was solved in the SN direction for all draw rate models. Table 2 shows the results of all models. The USD model is a comprehensive model because it has all other models' details. The obtained NPV from the USD is $47 M with the optimality gap of 4%. The total running time in this direction is 07:27:26. This time, according to the complex structure of the USD model, is desirable. The total extracted tonnage from all drawpoints is 30.1 Mt. This means that about 82% of all material is extracted in this model.

Fig.8 shows the production and average grade of production in each period for the USD draw rate model. It can be seen that the model attempts to deplete the drawpoints with a higher grade earlier. The average grade of production has a descending trend during the mine life. In period one, because of the minimum draw rate and total allowable active drawpoints, production is less than the maximum mining capacity. However, after period one the draw rate can deplete other draw rates according to PRC, so mining capacity reaches to the maximum boundary. During the last periods, because of reaching the top of the draw column and of the probability of dilution, the average grade of production is less than in previous years. But it also must be noted that dilution is reduced, because of the controlling feature of the production rate curve in the draw control system. The difference between the maximum grades in the first period and minimum one in the last period is less than 0.22%. By this way, the USD model can reduce dilution with respect to the draw control.

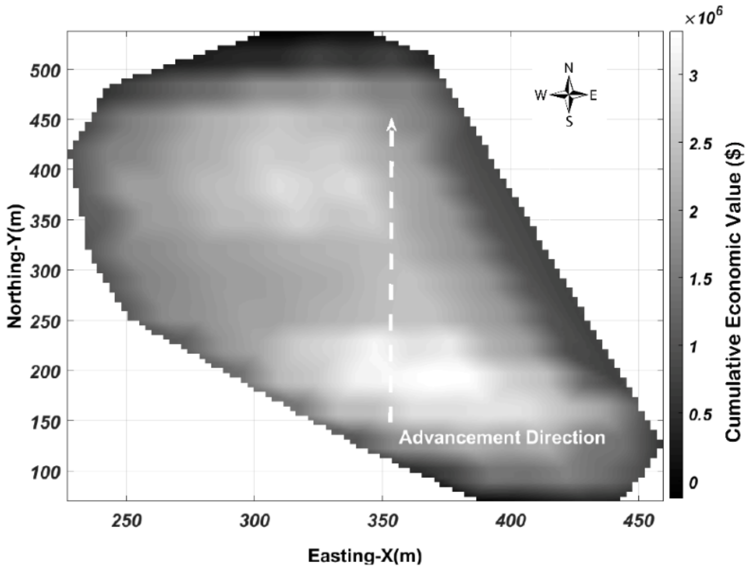


Fig. 7. Mining advancement direction

Table 2. Numerical results of all models

Model	CPU time	Total extraction (Mt)	Extraction (%)	NPV (M$)	Constraint number	Variable number	
						Con.	Bin.
USD	07:27:26	30.1	82	47.00	47257	4470	8940
US	12:20:21	30.3	82.6	47.02	42787	4470	8940
UD	26:15:18	29.3	79.8	45.81	42787	4470	8940
SD	02:25:12	29.4	80.1	47.99	38317	4470	8940

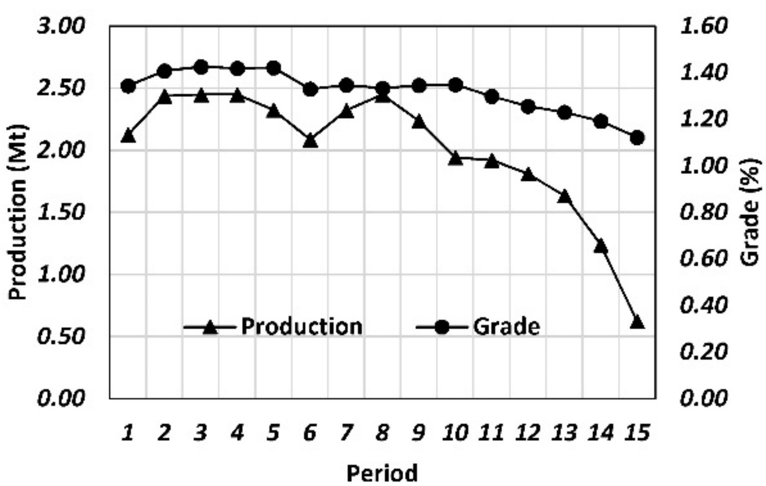


Fig.8. Production tonnage and average grade of the production in USD draw rate model

Fig. 9 shows the maximum number of active drawpoints in each period. The number of active drawpoints in period one is more than in other periods because depletion from all drawpoints must be within the minimum draw rate in the first period according to the minimum draw rate constraint. Hence it needs a greater number of active drawpoints in period one. Afterwards, during the next ten years, the mine works with maximum allowable active drawpoints. From periods 12 to 15, this number gradually reduces.

Fig. 10 illustrates the starting period of the drawpoints during the mine life. The maximum number of drawpoints is opened in period one. The number of started drawpoints in periods 6 and 11 is more than in other periods, except for period 1. This is because of the defined maximum activity period for each drawpoint, which is 5 periods.

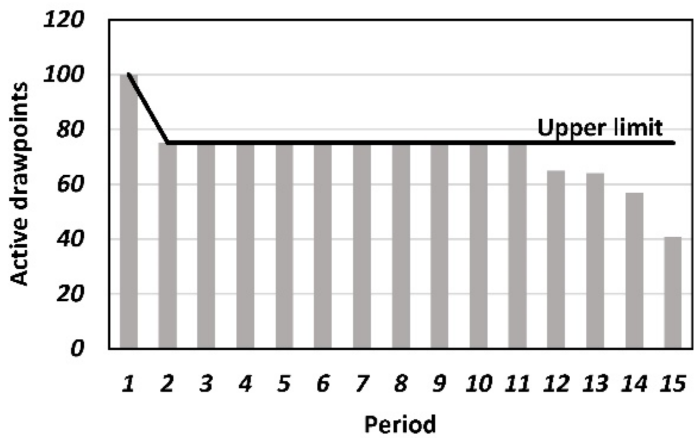


Fig. 9. Number of active drawpoints in each period during the mine life

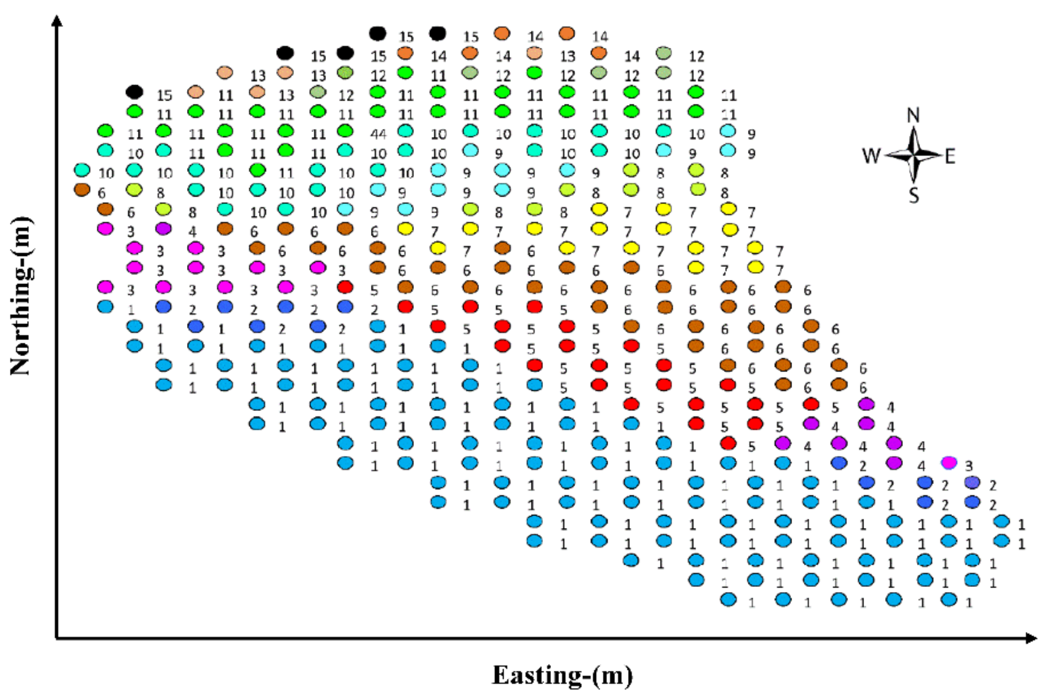
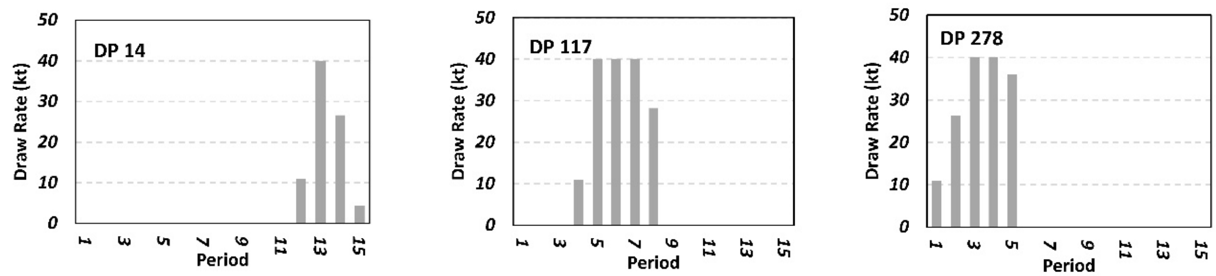


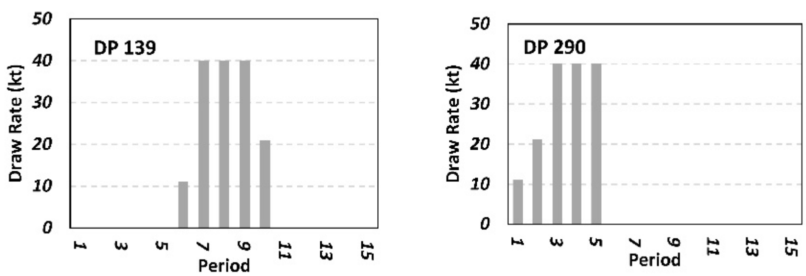
Fig. 10. Starting period of extraction from each drawpoint

According to the defined draw rate strategy (USD), drawpoints cannot be depleted arbitrarily, but it is possible because of the objective function and the constraints, the material with lower economic value remains in the number of drawpoints. Fig. 11 illustrates the draw rate changes for different drawpoints in the NS direction.

It is clear that the defined lower bound and the PRC for selected drawpoints are satisfied. For instance, extraction from DP 278 is started in period 1 with the minimum acceptable draw rate (11 kt), then it increases gradually to reach the maximum acceptable draw rate (40 kt) in period 3. After a steady extraction with the maximum draw rate for two periods, the draw rate drops. It can be seen that the tonnage of extraction from drawpoints varies based on the drawpoints' economic values because the objective function maximizes the NPV and the tonnage of extraction from each draw column is a result of optimization. One of the advantages of the draw control system is controlling the surface displacement by using the draw rate in all drawpoints during the mine life. The results show that all the defined constraints have been satisfied. The draw rate amount for each drawpoint and starting and finishing periods are obtained as a result of optimization. The model extracts the material from each draw column based on the defined draw rate model while maximizing the NPV of the operation.

In addition to the examination of the USD draw rate strategy, other draw rate models (US, SD, and UD) were also investigated with the same advancement direction. It is obvious that the value of the NPV for the SD strategy is higher than others because the tonnage of the material that can be depleted from the active drawpoints in early periods is higher than from other strategies. Table 3 summarizes the result of different strategies.





DP ID	Initial Tonnage (kt)	Extracted Tonnage (kt)	Extracted Tonnage (%)
14	82.00	82.00	100.0
117	169.15	159.15	94.1
139	157.35	151.95	96.6
278	174.83	153.35	87.7
290	169.06	152.15	90.0

Fig. 11. Obtained draw rate as a result of optimization for different drawpoints

Table 3. Numerical results for different draw strategies

Model	Initial Tonnage (Mt) & Direction	Extracted Tonnage (Mt)	NPV (M$)
USD	36.7 - SN	30.1	47.00
US	36.7 - SN	30.3	47.02
SD	36.7 - SN	29.4	47.99
UD	36.7 - SN	29.3	45.81

Fig. 12 shows the cash flow for different strategies. Fig. 13 shows the height of draw columns at the end of some periods for the USD draw rate strategy. The defined advancement direction has also been satisfied, as shown. The height of the drawpoints represents the surface displacement at the end of each period. One of the advantages of the draw control system is that it controls surface displacement by using the draw rate in all drawpoints during the life of the mine.

It is obvious that the cash flow during the first eight years of the mine life for the SD model is greater than that for other models. As shown in Table 3, the SD model has the highest NPV among other models because in the first periods it forces the model to deplete the material from the drawpoints with maximum draw rate. The US strategy has the higher NPV after the SD strategy. It can be seen that after period 11, the US strategy has higher cash flow than SD because there is no ramp-down periods for the US strategy. The lowest NPV belongs to UD strategy.

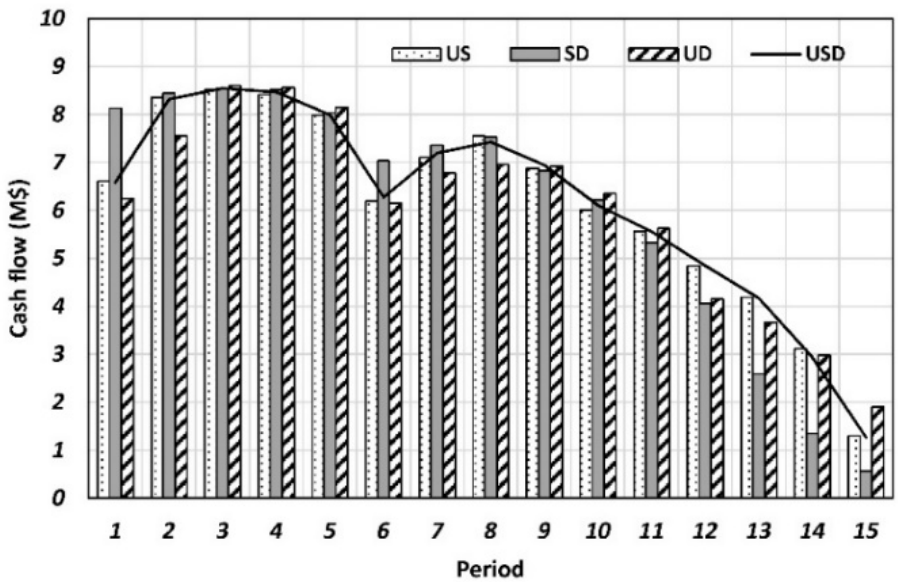


Fig. 12. Comparison of cash flow for all draw rate strategies

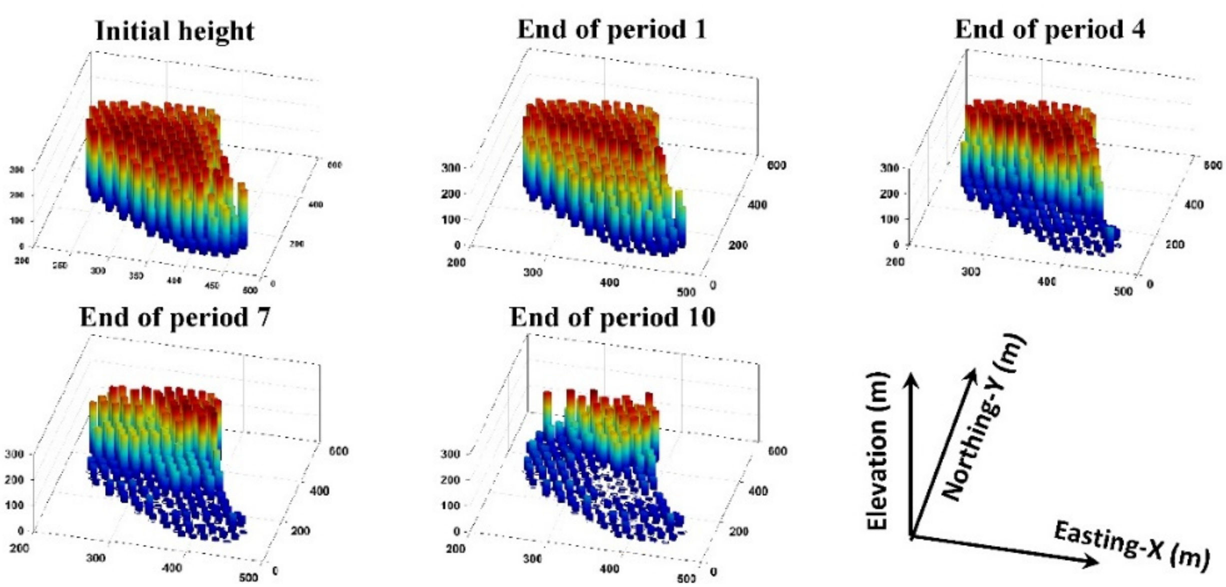


Fig. 13. Height of drawpoints at the end of periods 1, 4, 7, and 10 for the USD draw rate

6. Conclusion

This paper presented a mathematical draw control system for block-cave production scheduling optimization based on PRC. MILP formulation for block-cave production scheduling was developed, implemented, and tested in the CPLEX/IBM environment. The formulation maximizes the NPV subject to defined operational constraints. To manage drawpoint production, the PRC which limits production based on the amount of material that has been drawn previously was established. This means that production depends on the cumulative tonnes mined from a drawpoint.

The PRC was classified in four alternative general forms to be modeled and practiced by all mines according to their draw requirements. Among these four models, the USD model is a comprehensive model which can produce other models by changing depletion boundaries. Consequently, drawing pattern and dilution are controlled by using the introduced mathematical model. The surface displacement is controlled by using the defined draw rate in all drawpoints during the life of the mine.

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Stochastic Optimization of Block Cave Production Scheduling with Material Flow Uncertainty

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ABSTRACT

Block-cave mining has become more popular in the last few years, because of its lower operating costs and less waste removal requirements, the trend is expected to continue. Production scheduling, as one of the most important steps in any mining project, can be complicated for block caving mining because of the material flow and its uncertainties. The uncertainties should be considered within the production schedule, otherwise, the production schedule could be far from the real operations. This research uses stochastic optimization for production scheduling in block-cave mining. The proposed model maximizes the net present value of the mining project while minimizing the production grade deviations from a target grade. A number of scenarios are considered to capture the material flow uncertainties. Testing the model for a real case block-cave mining operation shows that the proposed model can take the material flow uncertainties into the production schedule in order to achieve more reliable plans; the optimum production schedule is accomplished based on different scenarios which can happen in the real operations. The model also calculates the optimum height of draw as part of the optimization.

1. Introduction

Any planning and financial analysis in a mining project depends on production schedule in which the amount of ore and waste removal in each period of time is determined. An optimum realistic production schedule can significantly improve the overall practicality and profitability of the project. Block-cave mining operation is involved with uncertainties which cannot be ignored in the production scheduling; while the caving is occurring, the flow of material (which happens because of the gravity) can be unpredictable. This will result in grade and tonnage uncertainties in the production during the life of mine. Numerical methods are useful tools to model the material flow. With stochastic optimization, it is possible to capture the uncertainty of material flow within the production schedule.

Production schedule in a block-cave mining operation can be investigated from different levels of resolutions: cluster level, drawpoint level, or slice level (Pourrahimian, et al., 2013). In this research, the slices are the smallest production units. The output of the production schedule at this level would be the periods in which each of the slices within a draw column is extracted and sent to the processing plant. These decisions are made based on the defined goal(s) in the objective function while considering the limitations of the operations as the constraints of the model. The proposed production scheduling model is a stochastic optimization model in which the net present value of the project is maximized during the life of the mine while the deviations from a target production grade are minimized. Different scenarios of grades for the slice model are generated to analyze the uncertainty of the production grade which exists because of the material flow during production.

2. Block caving

These days, most surface mines work in a higher stripping ratio than in the past. In the following conditions, a surface mine can be less attractive to operate and underground mining is used instead: (i) too much waste has to be removed in order to access the ore (high stripping ratios), (ii) waste storage space is limited, (iii) pit walls fail, or (iv) environmental considerations could be more important than exploitation profits (Newman, et al., 2010). Among underground methods, block-cave mining, because of its high production rate and low operation cost, could be considered an appropriate alternative. Projections show that 25 percent of global copper production will come from underground mines by 2020. Mining companies are looking for an underground method with a high rate of production, similar to that of open-pit mining. Therefore, there is an increased interest in using block-cave mining to access deep and low-grade ore bodies. A schematic view of block cave mining is shown in Fig 1.

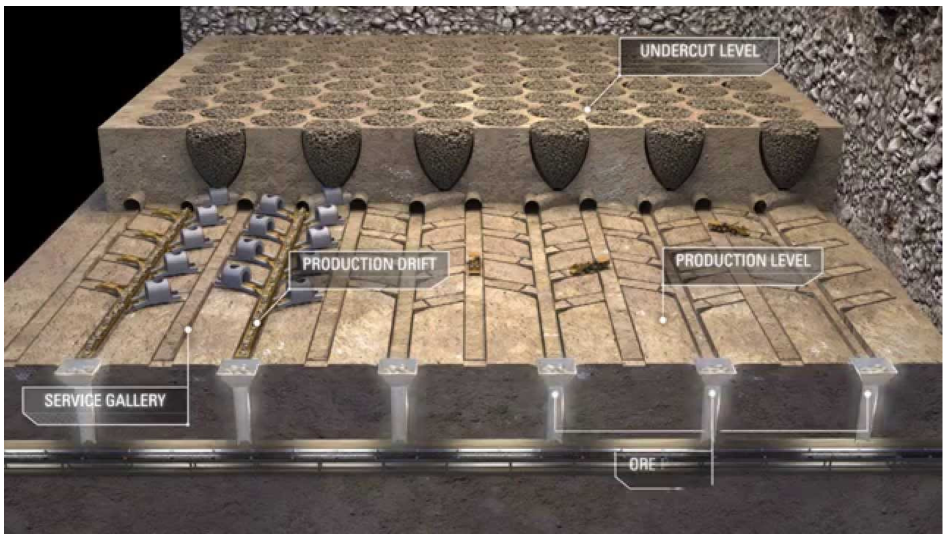

Fig 1. Block cave mining, LHD method (Caterpillar, 2015))

3. Literature review

There is a significant amount of research on production scheduling in mining operations, mostly in open-pit mining (Newman, et al., 2010). In block-cave mining, the production schedule determines which drawpoints to be opened/closed in each period, which slices to be extracted, what the best direction for mining development is, and what is the production rate and the production grade during the life of mine. A detailed literature review of production scheduling in block-cave mining can be found in (Khodayari & Pourrahimian, 2015).

Production scheduling in block-cave mining is more complicated to be optimized, mainly because of the material flow and its uncertainties. Researchers have also been trying to model the flow of material and how it can impact the production in cave mining for almost three decades. Numerical models (Alford (1978); R. L. Castro, et al. (2009); Edward Pierce (2010)), pilot tests (Raúl L. Castro, et al. (2014);Jin, et al. (2017)), and full scale experiments (Power (2004); Brunton, et al. (2016); Garcés, et al. (2016)) have been used to study the flow of the material. Pilot models have many limitations and in most cases cannot describe the behavior of the flow. Full-scale methods are usually expensive to use. Numerical models can be more efficient and less expensive if they are properly modeled. Gibson (2014) tried to use Pascal cone to understand the probabilities of blocks moving down as the production occurs in caving operations. Although his model was dependent on the cell size and the probabilities, it was shown that stochastic models can be used to present the behavior of material flow.

This research proposes a stochastic optimization model in which, the uncertainty of the material flow which results in production grade uncertainty, is brought to the production scheduling optimization. This optimum production schedule will not only maximize the NPV of the project but also minimizes the deviation of the production grade from a target grade in the considered scenarios.

4. Modeling

The proposed model maximizes the NPV of the mining project during the life of mine while trying to minimize the deviations of production grade from a defined target grade. To be able to capture the uncertainty of production in block-cave mining, the model is a stochastic optimization in which different scenarios are considered. The formulation of the objective function was inspired by a stochastic optimization model which was used by MacNeil and Dimitrakopoulos (2017) for determining the optimal depth of transition from open pit to underground mining. The scenarios are defined based on the grade distribution in the mine reserve. Each scenario represents one circumstance that can happen during the production based on the flow of the material. Fig 2 shows the flow of the material and how it can impact the production.

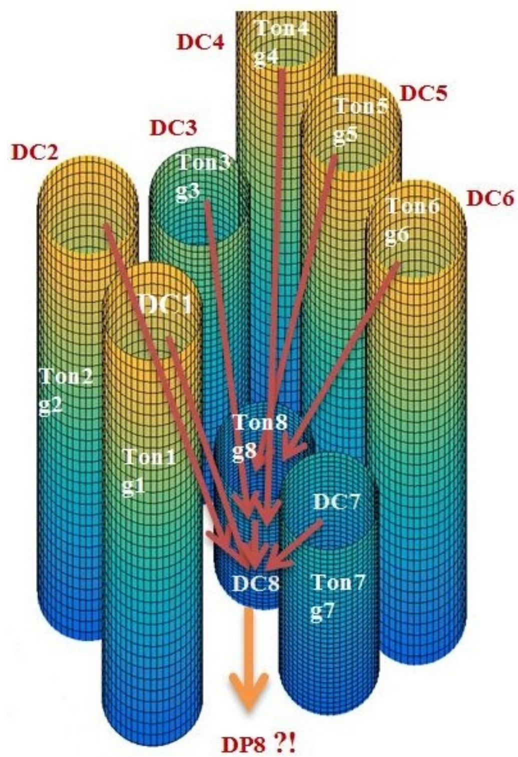

Fig 2. Flow of the material and its impact on the production grade

It can be seen that while extracting from a drawpoint, the material can move not only from the column above (DC8) but also from the columns in its neighborhood (DC1… DC7) into the intended drawpoint. This kind of movements of material during the caving is the main source of the uncertainties in the operations. A production schedule would be more realistic if the uncertainties are captured; this research's aim is to optimize the production schedule while capturing the material flow uncertainties. As it was mentioned, the decision units for the production schedule are the slices; the slice model is built based on the estimated block model, the column above each drawpoint is divided into slices. In this section, the mathematical programming model is presented in details.

4.1. Notation

- **Indices**

$t \in \{1,...,T\}$ Index for scheduling periods

$sl \in \{1,...,Sl\}$	Index for individual slices
$dp \in \{1,...,Dp\}$	Index for individual drawpoints
$s \in \{1,...,S\}$	Index for individual scenarios
$a \in \{1,...,A\}$	Index for the adjacent drawpoints

- **Variables**

$X_{sl}^{t} \in [0,1]$	Binary decision variable that determines if slice *sl* is extracted in period *t* [$X_{sl}^{t} = 1$] or not [$X_{sl}^{t} = 0$]
$Y_{dp}^{t} \in \{0,1\}$	Binary decision variable which determines whether drawpoint *dp* in period *t* is active [$DpAct_{dp}^{t} = 1$] or not [$DpAct_{dp}^{t} = 0$]
$Z_{dp}^{t} \in \{0,1\}$	Binary decision variable which determines whether drawpoint *dp* till period *t* (periods 1, 2,..,t) has started its extraction [$DpStart_{dp}^{t} = 1$] or not [$DpStart_{dp}^{t} = 0$]
$d_{us}^{t} \in \{0,\infty\}$	Excessive amount from the target grade (the metal content)
$d_{ls}^{t} \in \{0,\infty\}$	Deficient amount from the target grade (the metal content)

- **Model Parameters**

g_{sl}	Copper (Cu) grade of slice *sl*
g_{E}	Expected copper grade based on all scenarios
ton_{sl}	Ore tonnage of slice *sl*
t_{c}	Current period
sl_{dp}	Number of slices associated with drawpoint *dp*

- **Input Parameters**

$TarGrade$	The target grade of production which is defined based on the production goals and processing plant's requirements
$M_{\min}$	Minimum mining capacity based on the capacity of plant and mining equipment
$M_{\max}$	Maximum mining capacity based on the capacity of plant and mining equipment
$ActMin$	Minimum number of active drawpoints in each period
$ActMax$	Maximum number of active drawpoints in each period
M	An arbitrary big number
MinDrawLife	Minimum drawpoint life
MaxDrawLife	Maximum drawpoint life
DR_{Min}	Minimum draw rate

DR_{Max}	Maximum draw rate
$IntRate$	Discount rate
$RampUp$	Ramp up
$ScenNum$	Number of scenarios
$DP_{dp}^{t_c}$	Drawpoint depletion percentage which is the portion of draw column *dp* which has been extracted from drawpoint *dp* till period t_c
Price	Copper price (\$/tonne)
Cost	Operating cost (\$/tonne)
C_u	Cost (penalty) for excessive amount (\$)
C_l	Cost (penalty) for deficient amount (\$)

4.2. Objective function

The objective function is defined as follows:

$$\begin{aligned}
&Maximize \ \sum_{t=1}^{T}\sum_{sl=1}^{Sl} E\{(NPV_{sl}^{t})\}X_{sl}^{t} - \sum_{t=1}^{T}\sum_{s=1}^{S}\{Grade\ deviations\}_{s}^{t} \\
&= \sum_{t=1}^{T}\sum_{sl=1}^{Sl} \frac{(Price \times Rec \times (g_{Esl} \times ton_{sl}/100)) - (Cost \times ton_{sl})}{(1+IntRate)^{t}} * X_{sl}^{t} \\
&- \sum_{t=1}^{T}\sum_{s=1}^{S}\frac{1}{S}\left(\frac{d_{ls}^{t}\times c_{l} + d_{us}^{t}\times c_{u}}{(1+IntRate)^{t}}\right)
\end{aligned} \tag{1}$$

The first part of the objective function maximizes the NPV of the project during the life of mine, which is the optimum sequence of extraction of the slices in the mine reserve. The second part minimizes the deviations of the production grade from the target grade by allocating a penalty to the deviations that might happen in different scenarios.

4.3. Constraints

Operational and technical constraints of block-cave mining operations are considered to control the outputs of the optimizations model. Number of decision variables depends on the number of drawpoints and the number of slices in each drawpoint.

- *Logical constraints*

There are two sets of binary decision variables in the proposed model, which will be required for defining different constraints. Logical constraints connect the continuous decision variables to the binary ones; each set contains two inequality equations.

$$\text{Set 1: } Y_{dp}^{t} \in \{0,1\}, \begin{Bmatrix} dp \in Dp \\ t \in T \end{Bmatrix}$$

$$\forall t \in T \ \&\ dp \in Dp \rightarrow \quad Y_{dp}^{t} - M * \sum_{sl=1}^{sl_{dp}} X_{sl}^{t} \le 0 \tag{2}$$

$$\forall t \in T \ \&\ dp \in Dp \rightarrow \quad \sum_{sl=1}^{sl_{dp}} X_{sl}^{t} - M * Y_{dp}^{t} \le 0 \tag{3}$$

$$\text{Set 2: } Z_{dp}^{t} \in \{0,1\}, \begin{Bmatrix} dp \in Dp \\ t \in T \end{Bmatrix}$$

$$\forall\, dp \in Dp \rightarrow DP_{dp}^{t_c} = \sum_{t=1}^{t_c} Y_{dp}^{t} \tag{4}$$

$$\forall t \in T \ \&\ dp \in Dp \rightarrow \quad DP_{dp}^{t_c} - M * Z_{dp}^{t} \le 0 \tag{5}$$

$$\forall t \in T \ \&\ dp \in Dp \rightarrow \quad Z_{dp}^{t} - M * DP_{dp}^{t_c} \le 0 \tag{6}$$

- *Mining Capacity*

Mining capacity is limited based on the production goals and the availability of equipment.

$$\forall t \in T \rightarrow \quad M_{\min} \le \sum_{sl=1}^{Sl} ton_{sl} \times X_{sl}^{t} \le M_{\max} \tag{7}$$

- *Production grade*

This constraint ensures that the production grade is as close as possible to the target grade in different scenarios. The deviations from the target grade for all scenarios in different periods of production during the life of mine are considered for this constraint.

$$\forall t \in T \,\&\, \forall s \in S \rightarrow \quad \sum_{sl=1}^{Sl} (g_{sl} - G_{tar}) \times ton_{sl} \times X_{sl}^{t} + d_l - d_u = 0 \tag{8}$$

- *Reserve*

This constraint makes sure that not more than the mining resources can be extracted, the output of the model would be the mining reserve.

$$\forall sl \in Sl \rightarrow \quad \sum_{t=1}^{T} X_{sl}^{t} \le 1 \tag{9}$$

- *Active drawpoints*

A limited number of drawpoints can be in operation at each period of time; the mining layout, equipment availability, and geotechnical parameters can define this constraint.

$$\forall t \in T \rightarrow \quad ActMin \le \sum_{dp=1}^{Dp} Y_{dp}^{t} \le ActMax \tag{10}$$

- *Mining precedence (horizontal)*

The precedence is defined based on the mining direction in the layout. Production from each drawpoint can be started only if the drawpoints in its neighborhood which are located ahead (based on the mining direction) are already in production. Equation (11) presents this constraint.

$$\forall dp \in Dp \ \ \&\ \ t \in T \rightarrow \quad A * Z_{dp}^{t} \le \sum_{a=1}^{A} Z_{a}^{t} \tag{11}$$

Where *A* is the number of drawpoints in the neighborhood of drawpoint *dp* which are located ahead (based on the defined direction) and *Z* is the second set of binary variables.

- *Mining precedence (vertical)*

The sequence of extraction between the slices within the draw columns during the life of the mine is defined by this constraint.

$$\forall dp \in Dp \ \ \& \forall sl \in Sl \ \ \& \ \ t \in T \rightarrow \qquad X_{sl}^{t} \leq \sum_{t=1}^{t_c} X_{sl-1}^{t} \tag{12}$$

This equation ensures that in each period of t, slice *sl* in the draw column associated with drawpoint *dp,* is extracted only if slice *sl-1* beneath it is already extracted in the periods before or at the same period t_c.

- *Continuous mining*

This constraint guarantees a continuous production for each of the drawpoints during the life of mine. In other words, if a drawpoint is opened, it is active in consecutive years (with the minimum draw rate of DR_{Min}) till it is closed.

$$\forall dp \in Dp \,\&\, t \in T \rightarrow \qquad Y_{dp}^{t} \leq DpAct_{dp}^{t-1} + (1 - Z_{dp}^{t}) \tag{13}$$

- *Draw rate*

The total production of each drawpoint in each period of t is limited to a minimum and maximum amount of draw rate.

$$\forall dp \in Dp \,\&\, t \in T \rightarrow \qquad DR_{Min} \times Y_{dp}^{t} \leq \sum_{sl=1}^{sl_{dp}} ton_{sl} \times X_{sl}^{t} \leq DR_{Max} \tag{14}$$

- *Draw life*

Drawpoints are allowed to be in operation during a certain period of time which is called draw life. The draw life is limited to the minimum and maximum years of operations by the following equation:

$$\forall dp \in Dp \rightarrow \qquad MinDrawLife \leq \sum_{t=1}^{T} Y_{dp}^{t} \leq MaxDrawLife \tag{15}$$

5. Solving the optimization problem

The proposed stochastic model has been developed in MATLAB (TheMathWorksInc., 2017), and solved in the IBM ILOG CPLEX environment("IBM ILOG CPLEX Optimization Studio," 2017) CPLEX uses branch-and-cut search for solving the problem to achieve a solution within the defined mip gap (or the closest lower gap). The case study in this research was solved by gap of 3% (a feasible integer solution proved to be within three percent of the optimal).

6. Case study

The proposed model was tested on a block-cave mining operation with 102 drawpoints. It was a copper-gold deposit with the total ore of 22.5 million tonnes and the weighted average grade of 0.85% copper. The draw column heights vary from 320 to 351 meters. Fig 3 and Fig 4 show the drawpoints layout (2D) and a conceptual view of the draw columns (3D). Each draw column consists of slices with the height of 10 meters (33 to 36 slices for each draw column). In total, the model was built on 3,470 slices. The mine life of 10 years with the maximum production of 2 million tonnes of ore per year was considered. The details of the input parameters for the case study are presented in Table 1.

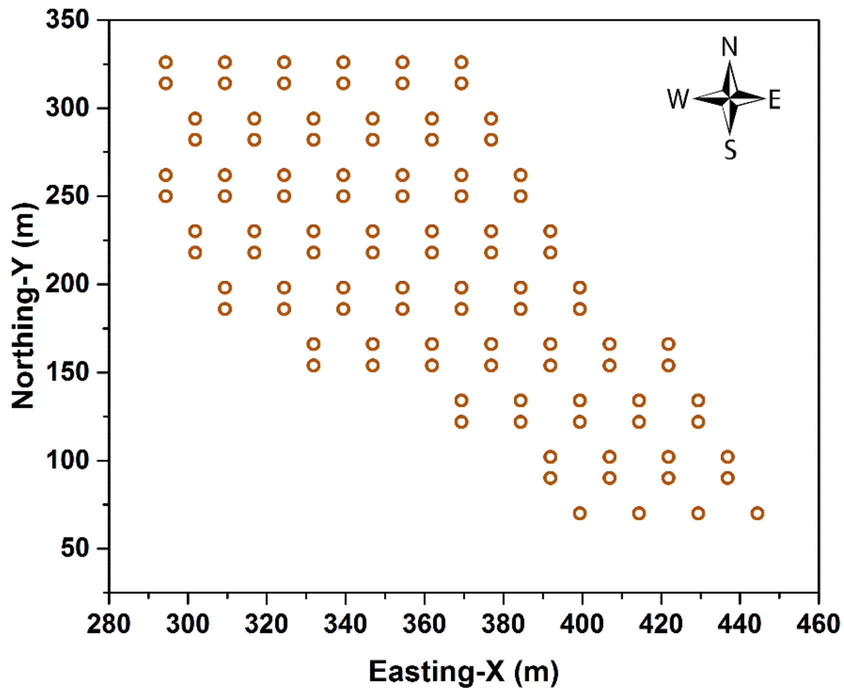

Fig 3. Drawpoints layout (circles represent drawpoints)

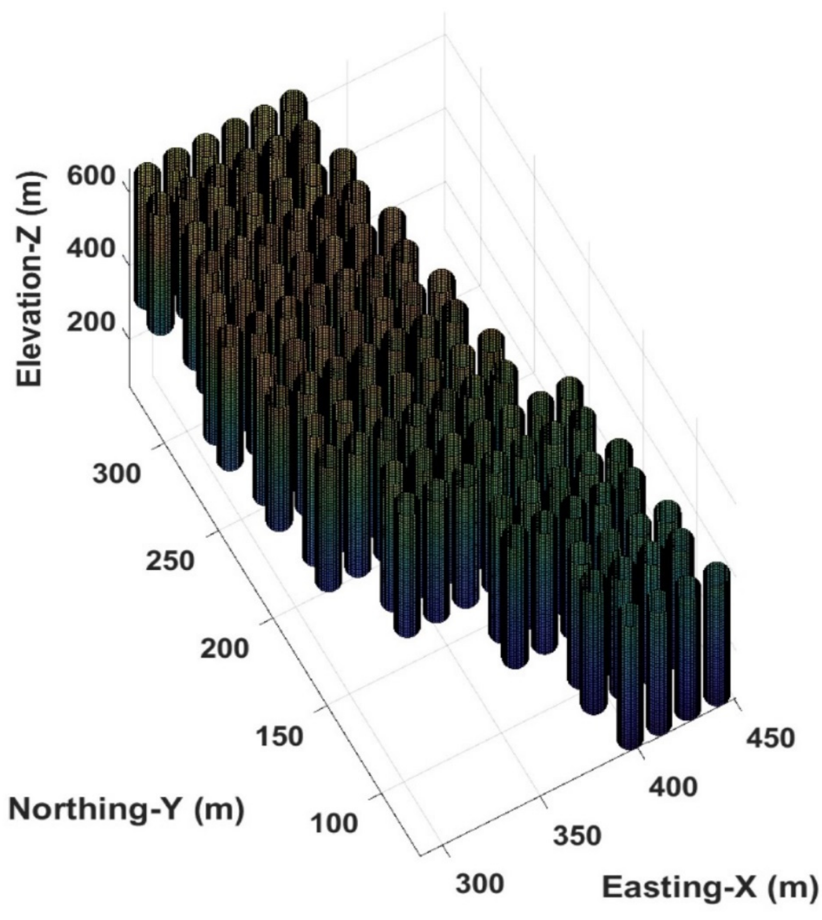

Fig 4. A conceptual view of the draw columns

Table 1. Scheduling parameters for the case study

Parameter	Value	Unit	Description
T	10	Year	Number of periods (life of the mine)
G_{min}	0.5	%	Minimum production average grade for Cu per each period
G_{max}	1.6	%	Maximum production average grade for Cu per each period
G_{Tar}	1.3	%	Target production grade (Cu)
M_{min}	0	Mt	Minimum mining capacity per period
M_{st}	0.5	Mt	Mining capacity at the first year of production
M_{max}	2	Mt	Maximum mining capacity per period
Ramp-up	3	Year	The time period in which the production is increased from starting amount to maximum
ActMin	0	-	Minimum number of active drawpoints per period
ActMax	70	-	Maximum number of active drawpoints per period
MIPgap	5	%	Relative tolerance on the gap between the best integer objective and the objective of the best node remaining
Radius	8.2	m	The average radius of the drawpoints
Density	2.7	t/m^3	The average density of the material
M	100	-	An arbitrary big number
MinDrawLife	0	Year	Minimum life of drawpoints
MaxDrawLife	4	Year	Maximum life of drawpoints
DR_{Min}	13,000	Tonne/year	Minimum draw rate
DR_{Max}	75,000	Tonne/year	Maximum draw rate
Recovery	85	%	Recovery of the processing plant
Price	5,000	\$/tonne	Copper price per tonne of copper
Cost	15	\$/tonne	Operating cost per tonne of ore (Mining+Processing)
IntRate	10	%	Discount rate
S	50	-	Number of scenarios

In this case study, different scenarios were defined by generating random numbers in MATLAB; a linear function was defined based on the original grades of the slices to produce different scenarios. The model was built in MATLAB (R2017a) and solved using IBM/CPLEX (Version 12.7.1.0). Also, the model was solved as a deterministic model in which there was no penalty for deviation from defined target grade. The production grade in different scenarios (stochastic model) and deterministic model is shown in Fig 5. It can be observed that in all scenarios the production grade is as close as possible to the defined target grade during the life of mine. The deterministic model tries to maximize the NPV and the higher-grade ore is extracted at the first years of production and then the lower grades at the latter years. Ore production is regulated by the mining capacity constraint and the ramp-up and ramp-down are almost achieved in both stochastic and deterministic models (Fig 6 & Fig 7).

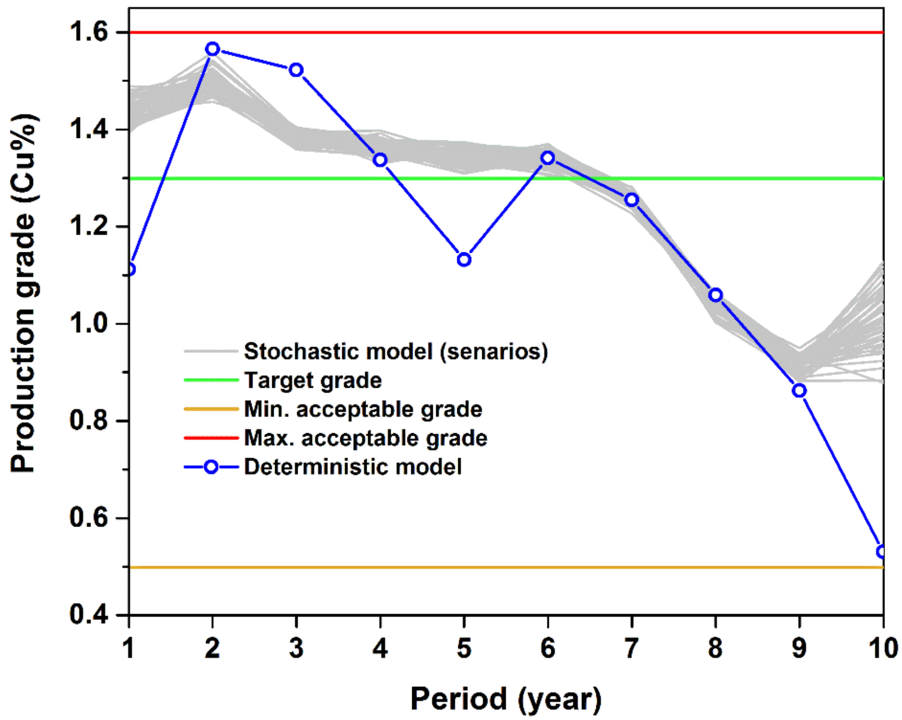

Fig 5. Average production grade based on the stochastic and deterministic models

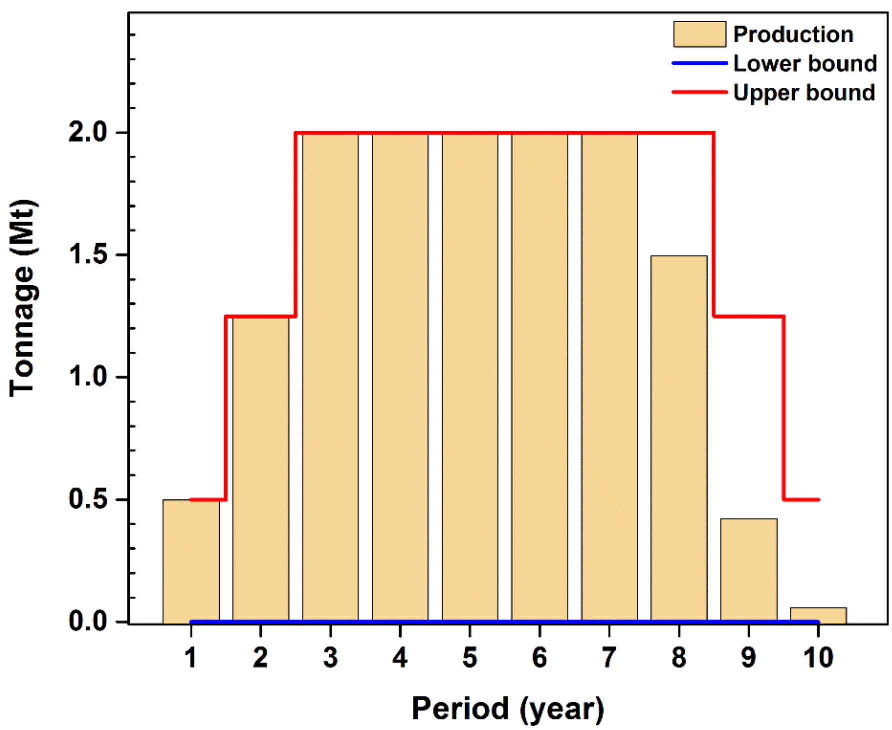

Fig 6. Ore production during the life of mine (stochastic model)

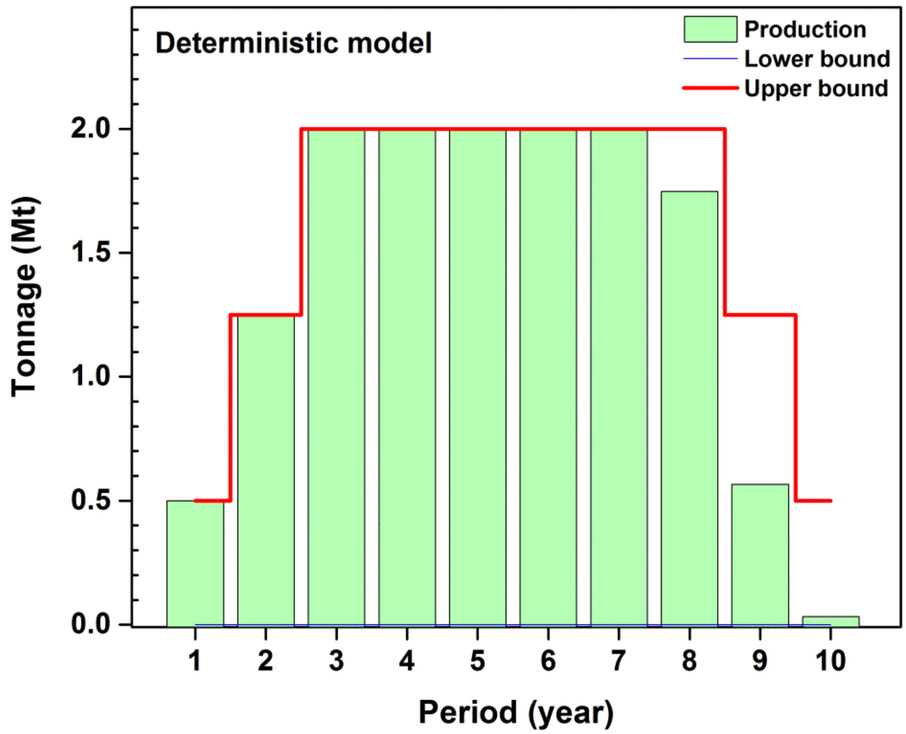

Fig 7. Ore production during the life of mine (deterministic model)

Horizontal precedence, which is the sequence of extraction between drawpoints, was achieved for both of models based on the defined v-shaped precedence (Fig 8).

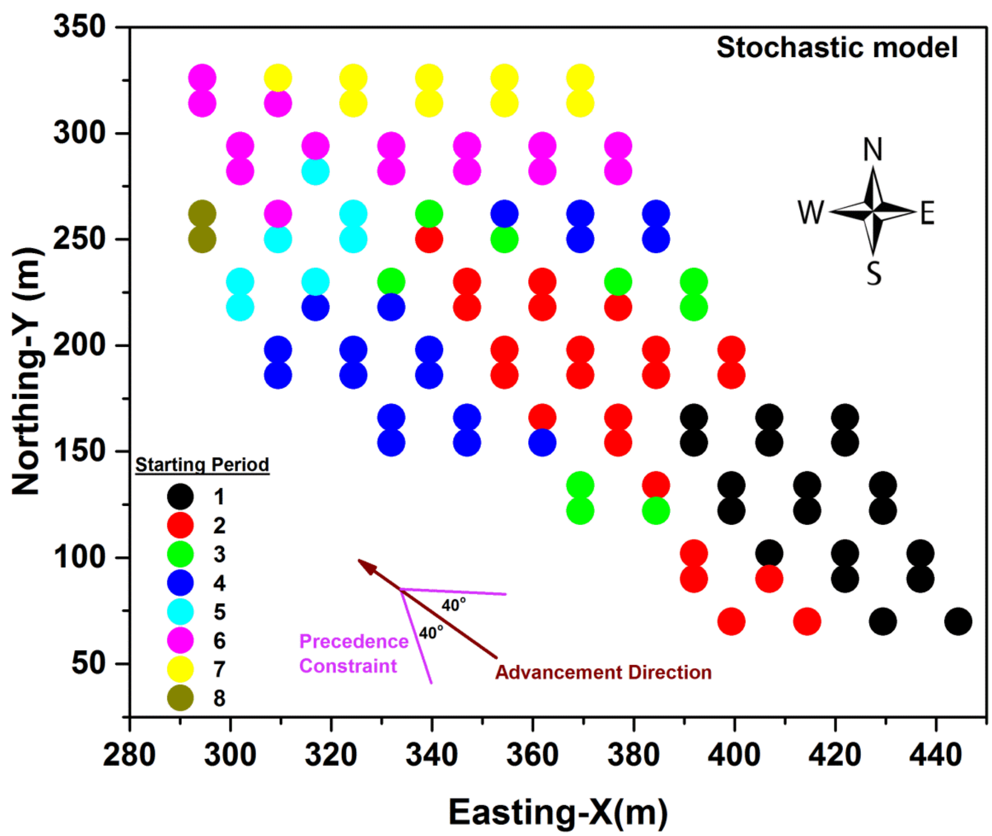

Fig 8. Sequence of extraction for drawpoints based on the stochastic model (2D precedence)

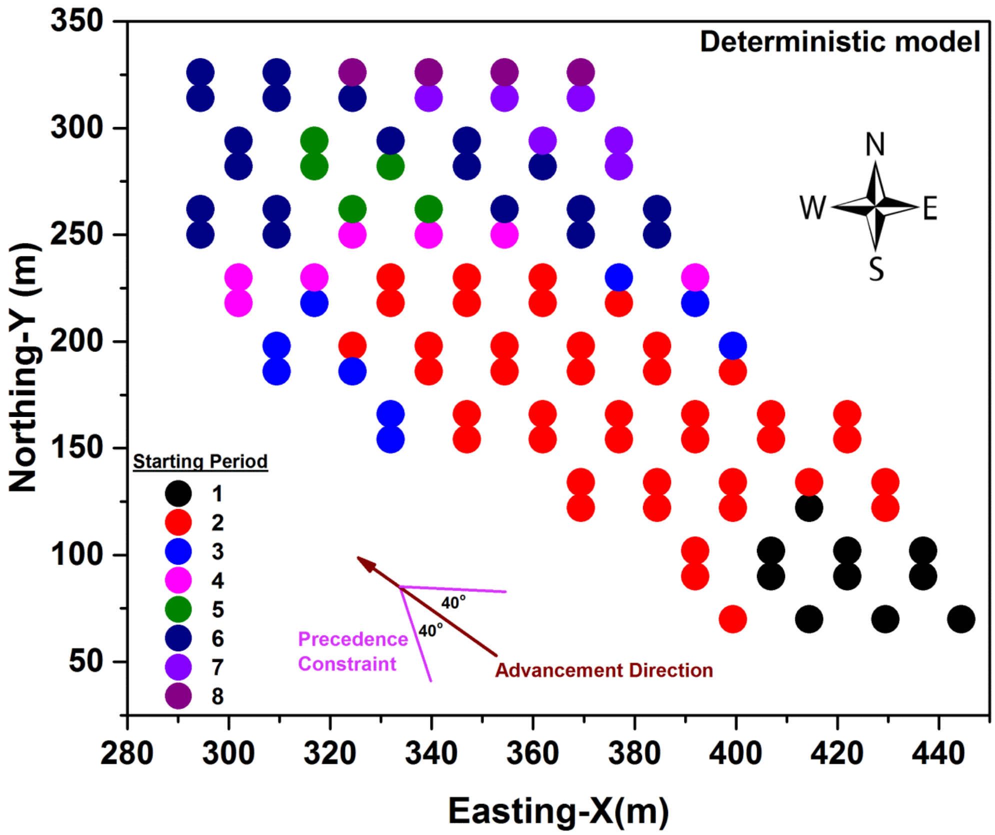

Fig 9. Sequence of extraction for drawpoints based on the deterministic model (2D precedence)

Vertical precedence determines the sequence of extraction between slices in each of draw columns. Fig 10 shows the sequence of extraction in draw column 75. It can be seen that extraction from this drawpoint starts from year 5 and ends at year 8; the sequence of extraction is well maintained and the production is continuous which means both the vertical precedence and continuous mining constraints were satisfied. The original height of draw column 75 is 330.1 meters with the total ore of 212,397 tonnes which contains 34 slices. Based on the optimization results (Fig 10), the optimum height of draw (best height of draw) was 260 meters with the optimum draw tonnage of 168,650; this means that 26 out of 34 slices are extracted during the life of mine.

Number of active drawpoints and number of new drawpoints which are opened in each year for both models are presented in Fig 12 and Fig 13. Comparing the new drawpoints to be opened in each year for two models, the stochastic model does not suggest big changes from one year to another while the deterministic model shows such a pattern. In other words, the results of the stochastic model is more practical than the deterministic model.

A brief comparison among the original ore resource model, the results of the deterministic model, and the results of the stochastic model is presented in Table 2. For this case study, the mining reserve and the NPV of the project for both models are almost the same (-2% in ore reserve and 0.7% for NPV). The stochastic model takes longer to solve, it is because of the number of decision variables and also the number of constraints. The stochastic model has more decision variables because of the deviation variables and more constraints for of the scenarios.

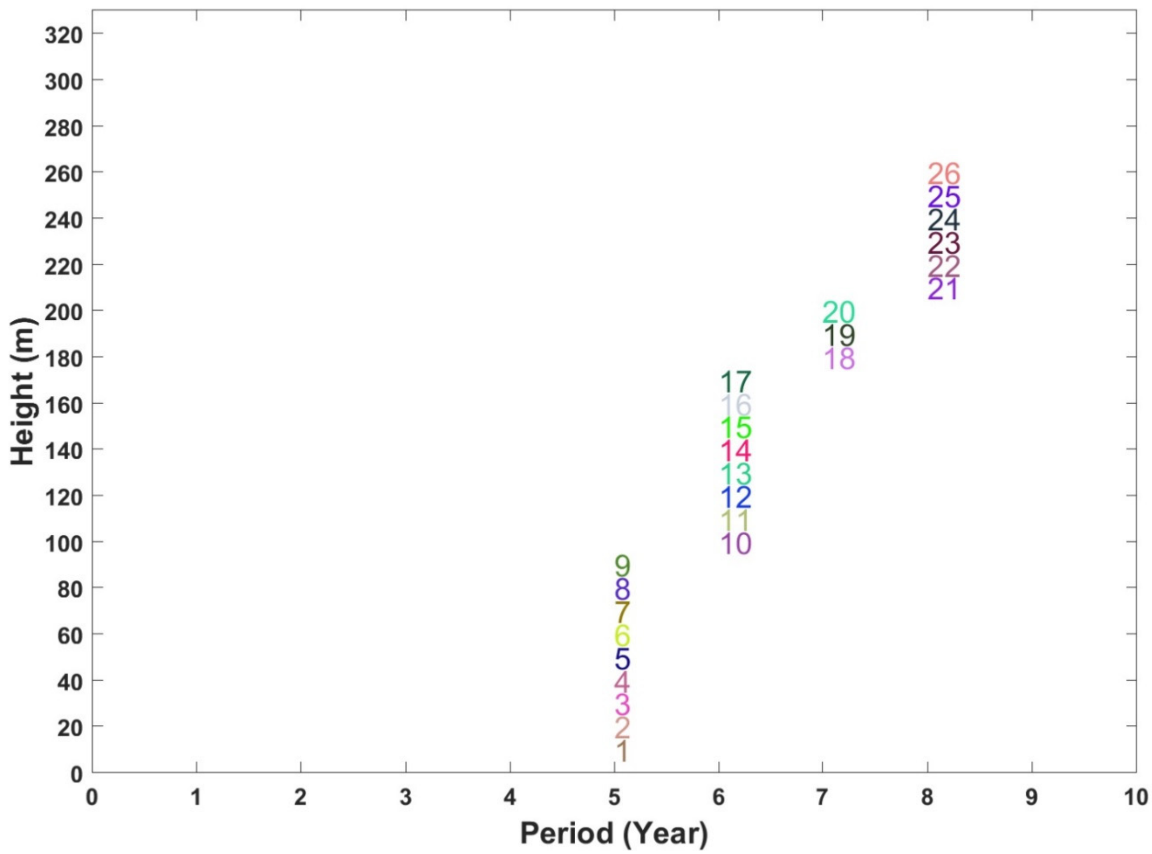

Fig 10. Sequence of extraction for slices in draw column associated with drawpoint 75 (numbers represent ID of slices within the draw column)

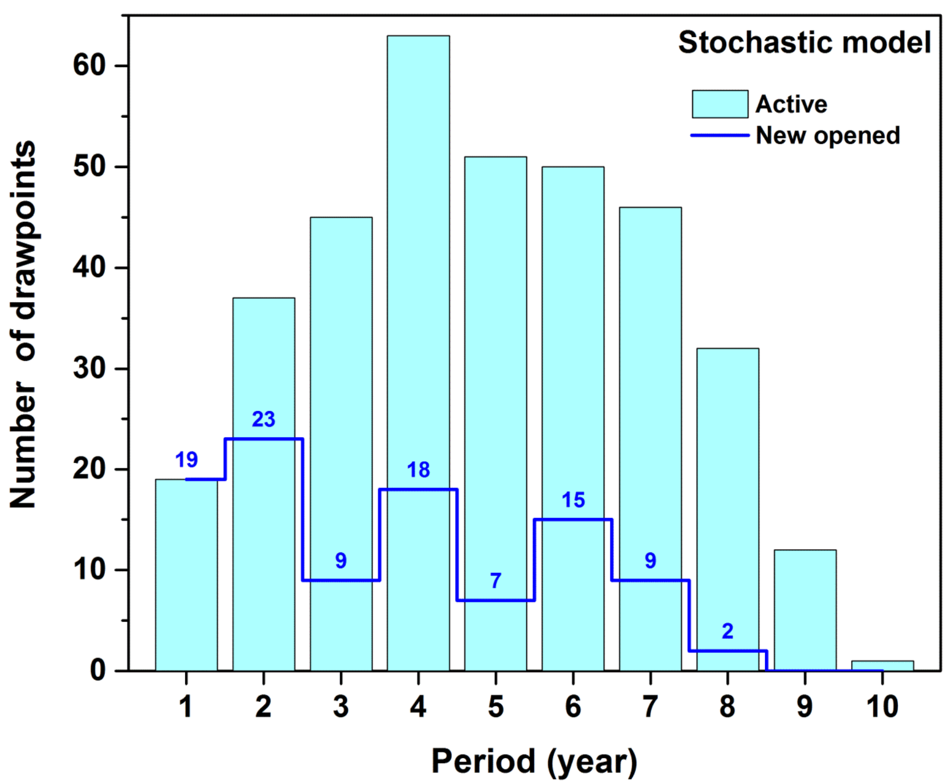

Fig 11. Active and new opened drawpoints for the stochastic model

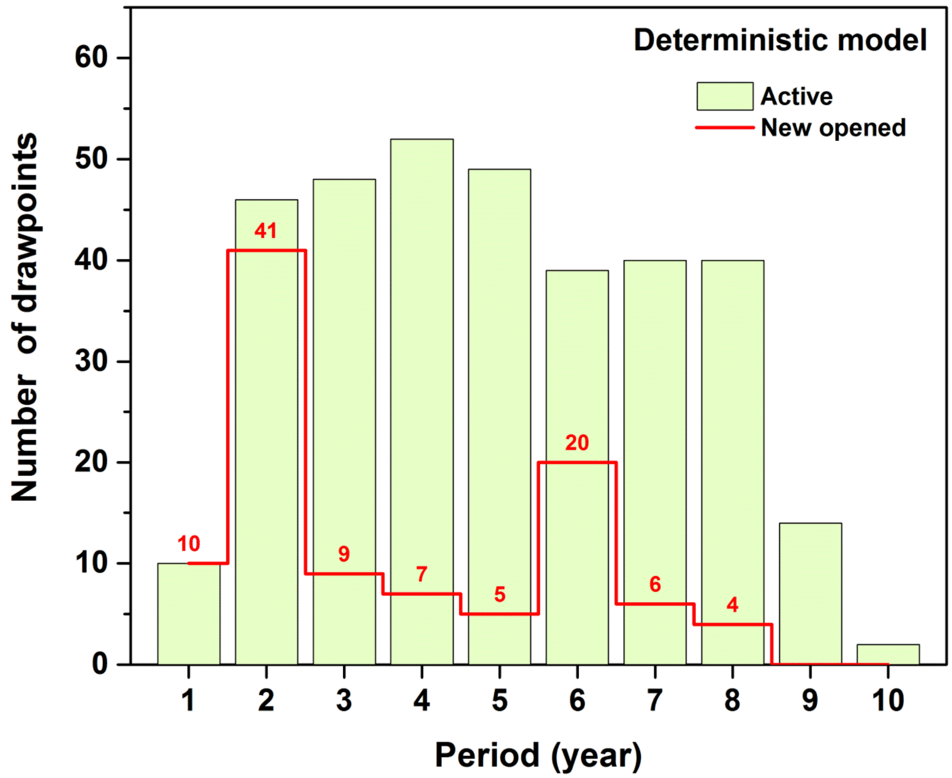

Fig 12. Active and new opened drawpoints for the deterministic model

Table 2. Comparing the original model with the deterministic and stochastic models results

Comparison item	Original Model (Mine Resource)	Mine Reserve	
		Deterministic Model	Stochastic Model
Ore tonnage (Mt)	22.5	14	13.7
Number of slices	3,470	2,160	2,106
Average weighted grade (%)	0.85	1.28	1.3
Height of draw in individual draw columns	320-351	30-320	30-310
Number of slices in individual draw columns	33-36	3-32	3-31
NPV (M$)	-	357.1	359.7
Solution time (Seconds)	-	5,292	55,601

7. Discussion

Production scheduling for block-cave mining operations could be hard because of the uncertainties which are involved in the operations. A stochastic optimization model was proposed in this research in order to maximize the NPV of the project while minimizing the production grade deviations from the project's targets. Results show that stochastic models can be so effective in production scheduling for block-cave mining: the production goals are achieved, the constraints of the mining project are satisfied, the uncertainty of the material flow is captured, optimum height of draw (best height of draw) is calculated as part of optimization, as well as the net present value of the project is maximized. Unlike deterministic models which do not consider the uncertainty of the material flow, stochastic models can maximize the profitability of the project while minimizing the unexpected events. The future work will be on consideration of both grade and tonnage deviations in the production schedule, and also generating more realistic scenarios.

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An Application of Mathematical Programming for Conditional Draw Control Modeling in Block-Cave Mining

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ABSTRACT

Block caving is a complex and large-scale mining method. The application of block caving is for low-grade, caveable, and massive ore-bodies. Among the underground mining methods available, caving methods are favoured because of their low cost and high level of production. Generating a production schedule that will provide optimal operating strategies without geotechnic constraints is not practical in block caving. Some complex theories and mathematical draw control systems have been applied in block-cave mines. However, most did not use an exact production rate curve and depletion conditions among the draw column to manage draw rates of drawpoints in the caved area. Establishing relationships among draw columns to consider depletion rates of other draw columns is complex but essential to provide a reasonable solution for real block-caving mines. This paper presents a mixed-integer linear programming (MILP) model to optimize the extraction sequence of drawpoints over multiple time horizons of block-cave mines with respect to the draw control systems. Four resolutions are formulated in this paper to guarantee practical solutions with respect to draw control managing in mined areas according to the draw rate and conditional draw rate constraints. Dilution and caving are improved indirectly, because the method considers the draw rate strategies. Application and comparison of the four resolutions for production scheduling based on the draw control systems are presented using 325 drawpoints over 15 periods.

1. Introduction

Among the underground mining methods available, caving methods are favoured because of their low cost and high level of production. Block-caving operations generate a much smaller environmental footprint than equivalent open-pit operations because the volume of waste that needs to be moved and handled is much smaller.

Rubio [1] mentioned that block caving is a technique in which gravity is used in conjunction with internal rock stresses to fracture and break the rock mass into pieces that can be handled by miners. Rubio pointed out that block caving requires more detailed geotechnical investigations of the ore-body than do other methods in which conventional drilling and blasting are employed as part of the mine production. Apprehending different operational and geotechnical situations is fundamental to preform and control caving. Geotechnical condition in the form of an exact production rate curve (PRC) controls the draw system. Caveability, in the context of draw control, is primarily concerned with balancing caving rates and production. If draw rates are not controlled, either air gaps or damaging stress concentrations may occur. Stress is important because undercut advance rates must be maintained to prevent stress damage to the production level. Draw must also be maintained across the production level to ensure that local stress

This paper, in its entirety, is submitted for publication in International Journal of Mining, Reclamation and Environment (IJMRE).

concentrations and premature dilution entry do not occur [2]. The draw rate is a parameter that is related to the seismic activity and geotechnical hazard potential in caving [3]. Applying draw control to moderate stress distribution in a caved area is one of the most important aspects of draw management. If major problems are to be avoided, production rates have to be tuned to the rate of caving and should not be exceeded. Poor draw control early in the panel's life can, over time, result in compounding difficulties in draw, dilution, low utilization and ground control.

In general, draw control is fundamental to the success or failure of any block cave operations. If draw from the drawpoints is not controlled, many problems and hazards occur: unbalanced cave subsidence as a result of poor ground control over time, decreased recovery and productivity, premature waste ingress and recompaction of broken material in the draw columns, infrastructure instability, fragmentation size distribution, more dilution, ore handling difficulties that can lead to tunnel and ore pass collapse or haulage systems, flow of muck at the drawpoints, and other safety and financial or safety damage to miners. Consequently, a production planning program that does not incorporate the geotechnical properties of the rock mass within the block-cave mining method will not be used for general purposes of production schedules, since such a plan causes many forms of damage. Careful control of the production in long-term planning of a block-cave mine will ensure that the schedule drawing process within the cave moderates unwanted problems and preserves mining economics associated with production targets. Thus, draw control is a basic input and output of a block-cave mine to maximize a company's economic goals by taking into consideration the geotechnical properties of rock mass.

The main cause of over stresses at a cave front is related to the angle of draw, which affects the stress pattern at the cave front. The angle of draw is correlated with the collapses experienced at mines. It is well established that an even draw leads to a more uniform stress distribution on the production level than an isolated draw [4]. Draw control in caving operations has two critical responsibilities: (i) defining a pattern for all drawpoints to deplete by a specific PRC, and (ii) creating an appropriate relationship among all draw columns to adjust their depletion rate by considering adjacent drawpoints according to the caving direction.

This research intended to practice the above mentioned critical responsibilities in planning as an important element of the performance and productivity of a block-caving mine. In this paper some applicable algorithms have been developed to optimize draw control. In order to develop optimization techniques that have the ability to integrate actual planning, more investigation is needed. A strict schedule planning system is needed to maintain production control and implement an effective draw strategy once production commences. Introducing a draw control system based on mathematical programming that integrates constraints from other disciplines like geology, mining and metallurgy will become more acceptable as real business planning tools.

This paper establishes several constraints at different resolutions that can be applied to illustrate a draw control system's effects on mine planning: a draw rate constraint based on PRCs, conditional draw rate constraints, and a maximum number of active periods. These constraints are presented by a set of equations to ensure that the tonnage and grade of material drawn from a drawpoint will be in a practical, specified range. The first resolution seeks to model the exact draw rate constraint. The size and complexity of the mathematical formulation of PRC has forced researchers to consider only minimum and maximum boundaries for draw rate constraint instead of tracking a global model to define how the draw rate is adjusted between these boundaries.

The draw columns should be drawn homogenously across the cave to confirm that the ore-waste interface is maintained between draw columns. In an appropriate planning, difference in draw rate between adjacent drawpoints should not exceed from a specified range. High draw differentials between adjacent drawpoints can result in local problems of uneven mixing, and have the potential to promote packing and convergence in weaker ground [5].

In this paper the conditional draw rate is investigated at three resolutions: (i) draw rates of the considered drawpoint and its adjacent drawpoint along the advancement direction at period t (CDRAT) in which the difference in the draw rate between two drawpoints is controlled by the angle of the draw; (ii) draw rates of the considered drawpoint and its adjacent drawpoints based on the advancement direction at period t (CDRMT) in which difference of the draw rate among multiple drawpoints is controlled by the angle of the draw; and (iii) the difference in extracted tonnage from the considered drawpoint and its adjacent drawpoint along the advancement direction from the beginning of extraction until the end of period t (CDRB). An even draw does not require all of the drawpoints to produce at the same rate. But the drawing process for any drawpoint in a period or among drawpoints in all periods must follow a given rule or range. Minimizing draw variability directly results in a uniform draw and consequently the overall dilution is minimized and the life of the mine is extended.

Conditional draw rate (CDR) establishes a condition such that the extraction of high and low tonnage draw columns in a deterministic distance does not exceed a defined range.

2. Literature review

Most of the mining optimization models that have been developed for block-cave mines consider a special area in planning problems. The literature on draw control systems based on the PRC for block-caving operations is relatively new. Most of the models use simulation in consideration of PRC to evaluate production schedules. PCBC [6] provides a simulation implement to research and assess various production schedules. The literature does not contain clear examples of block-caving production scheduling using a mathematical approach that formulate a draw control system in the block cave according to the PRC. Most of the studies consider only upper and lower boundaries for draw rate in their modeling. Laubscher [7] found that dilution entry is a function of the variation in tonnages drawn from adjacent working drawpoints. Therefore, draw control should limit the relative draw rates between adjacent draw columns. A good draw strategy helps to prevent damaging stress concentration by maintaining an even draw across the panel and it delays dilution entry by prohibiting an isolated draw. It has been shown that rock fragments can travel a substantial distance in the horizontal direction if a differential draw profile is applied [2]. Khodayari and Pourrahimian [8] presented a comprehensive review of operations research in block caving. They summarized several authors' attempts to use different methods to develop methodologies for optimizing production scheduling in block-caving operations. Previous to modern algorithms and computational developments, block-caving scheduling problems, like other underground mining methods in their large size, seemed intractable when formulated in mathematical form, especially in the case of mixed-integer linear programming (MILP) problems. Table 1 summarizes the mathematical models used for block-cave scheduling.

Pourrahimian et al. [9-12] devised other applications of MILP to develop a practical optimization framework for caving production scheduling. They presented a multi-step method for the long-term production scheduling of block caving to overcome the size problem of mathematical programming models and to generate a robust practical near-optimal schedule. Their model aims to maximize the net present value (NPV) of the mining operation at three levels of resolution while the mine planner has control over defined constraints. These levels are: (i) aggregated drawpoints (cluster level); (ii) drawpoint level; and (iii) drawpoint-and-slice level. Pourrahimian attempted to find an optimal schedule for the life of the entire mine, solving simultaneously for all periods by considering all required constraints, but he did not consider geotechnical properties of rock mass through the draw rate constraint. Pourrahimian (2014) mentioned that the formulation tries to extract material from drawpoints with a draw rate within the acceptable range without considering a specific shape. Alonso-Ayuso et al. [13] considered a planning mixed-integer programming (MIP) medium range problem for the El Teniente mine in Chile to maximize NPV by introducing, explicitly, the issue of uncertainty. They presented good work about the stochastic version of the copper extraction planning problem under uncertainty in (volatile) copper prices and used only some operational constraints without taking into account the draw control mechanism.

Table 1. Mathematical models in block-cave production scheduling optimization

Researcher	Mining capacity	Production grade	Maximum active drawpoints	Precedence	Continuous extraction	New drawpoints	Reserves	Maximum activity life	Draw rate without PRC	Draw rate with PRC	Relative draw rate	Conditional draw rate	Objective function	Model	Publication date
Riddle[1] [15]							*						Profit base	Dynamic	1976
Chanda[2] [16]	*	*	*		*								Min. Grade fluctuation	MIP and simulation	1990
Guest [17]	*	*		*			*		*		*		Max. NPV	MIP	2000
Smith[3] [18]									*				Min. deviation of column heights from ideal	MIP - LP	2001
Rubio [19]			*	*	*	*	*	*	*				Max. NPV and Min. Dilution	MILP	2002
Rahal [20]				*					*		*		Minimization production from ideal draw	MILGP	2003
Rahal[4] [2]	*	*		*	*		*		*		*		Min. production from ideal draw	MILGP	2008
Weintraub[5] [21]	*			*	*								Max. profit	MIP	2008
Queyranne [22]	*	*	*	*	*								Max. NPV	MIP	2008
Smoljanovic [23]	*		*	*	*			*					Max. NPV	MILP	2011
Parkinson [24]	*	*		*	*				*				Max. NPV	IP	2012
Epstein [25]	*	*	*	*	*				*				Max. NPV	MIP	2012
Pourrahimian [12]	*	*	*	*	*	*	*		*				Max. NPV	MILP	2013
Alonso[6] [13]	*	*	*	*	*								Max. NPV	MIP	2014

[1] Riddle presented a dynamic programing model based on ore reserve and profit model.

[2] Chanda's model was in raise level.

[3] Smith presented a review about the importance of a draw control system in a block-cave.

[4] Rahal considered the production rate curve as a goal of programming in the objective function, and a few of the constraints had different descriptions but the same application as the marked constraints.

[5] Weintraub presented a clustering method according to marked parameters.

[6] Alonso studied the risk in the presented research.

All of these studies have concentrated on determining the optimum configuration of a block-caving operation. The main problems associated with the methods presented above can be summarized as follows: some of them did not incorporate, on a routine basis, operational performance to adjust medium and long-term plans because of loss of geotechnical rules in the modeling of actual draw management systems. Constraints must be appropriate with the mining method, objective function, and real geotechnical condition of the rock mass. Maximizing tonnage or mining reserves will not necessarily lead to maximum NPV without aggregation reserve and grade constraint to time dynamic behavior of the fundamental models in linking the mine planning parameters and draw rate curves.

During production, the only control is through the drawpoints. The rate at which material can be drawn from an individual drawpoint depends on several rock mass and design parameters such as equipment size, layout configurations, and stress transfer on the extraction level, haulage infrastructure, and seismic activity [14].

The draw control system is a critical key in the accurate design and operation of block-cave mines. Most of the previous research considers a series of simple definitions of the process of moving and drawing caved material from drawpoints. The researchers have modeled the draw rate constrains regardless of the production rate curves and only by defining lower and upper bounds. Deciding minimum and maximum draw rates of drawpoints is appropriate according to the principles of geotechnical rules in all previous studies. However, during the tire life of any drawpoint, the draw rate varies. The literature review shows that there is no prominent study that models the relationship between the depletion rates of drawpoints in block caving using a mathematical formulation. However, the lack of consideration given to the draw rate curve according to geotechnical rules and new conditional draw rate constraints in the caved area, in addition to the abuse of the objective function and non-optimized scheduling, causes a problematic caving progress. The objective of this study is to develop, implement, and verify a realistic optimization MILP framework for block-cave long-term production scheduling, whereby a mineral is extracted and prepared at a desired market specification, with the maximum economic return measured by NPV, and within acceptable operational constraints with respect to geotechnical rules and draw control management. Figure 1 shows a schematic view of a production rate curve. This profile is usually provided by the geotechnical team to consider many factors such as the engineering and geotechnical properties of the rock mass and safety issues in extraction.

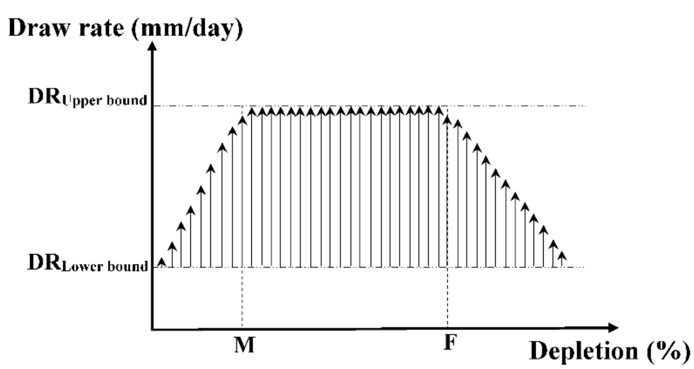

Figure 1. Production rate curve (ramp-up, high-production, and ramp-down)

3. Mathematical Formulation

Developing any mathematical model requires some decision variables, sets, indices, and parameters that correspond to a scheduling program. The following items are introduced according to the current mode:

Indices

$i \in \{1,...,I\}$	Index for drawpoints.
$t \in \{1,...,T\}$	Index for scheduling periods.
l	Index for a drawpoint belonging to set A^i .

Set

A^i	For each drawpoint i, there is a set A^i defining the predecessor drawpoints that must be started prior to the extraction of drawpoint *i*.
R^i	For each drawpoint *i*, there is a set R^i defining the adjacent drawpoints of the drawpoint *i*.

Decision variables

$X_{i,t} \in [0,1]$	Continuous decision variable, representing the portion of draw column *i* to be extracted in period *t*.
$E_{i,t} \in \{0,1\}$	Binary decision variable equal to 1 if drawpoint *i* is active in period *t*; otherwise it is 0.
$S_{i,t} \in \{0,1\}$	Binary decision variable controlling the precedence of extraction of drawpoints. It is equal to 1 if the extraction from drawpoint *i* is started in period *t*; otherwise it is 0.

Parameters

$Value_i$	Economic value of the draw column associated with drawpoint *i*.
$DR_{l,i,t}$	Minimum allowable draw rate of drawpoint *i* in period *t*.
$DR_{u,i,t}$	Maximum allowable draw rate of drawpoint *i* in period *t*.
$N_{Ei,t}$	Maximum allowable number of active drawpoints in period *t*.
$Num_{Nl,i,t}$	Lower limit for the number of new drawpoints, the extraction from which can start in period *t*.
$Num_{Nu,i,t}$	Upper limit for the number of new drawpoints, the extraction from which can start in period *t*.
Ton_i	Total tonnage of material within the draw column associated with drawpoint *i*.
M	Maximum allowable depletion to reach steady region after ramp-up.
F	Maximum allowable depletion to reach ramp-dawn region after steady region.
dsc	Discount rate.
MC_u	Upper limit of mining capacity in period *t*.
MC_l	Lower limit of mining capacity in period *t*.
Act_{life}	Maximum allowable periods that any drawpoints can be active.
$gr_{u,i,t}$	Upper limit of the acceptable average head grade of drawpoint *i* in period *t*.
$gr_{l,i,t}$	Lower limit of the acceptable average head grade of drawpoint *i* in period *t*.
$\widetilde{G}_{i,t}$	Average grade of drawpoint *i*.

DC	Diameter of draw column
□	Angle of draw
X_i , Y_i	Coordinates of drawpoint *i*.
UT	Upper bound of difference in tonnage between drawpoint *i* and *j*
LT	Lower bound of difference in tonnage between drawpoint *i* and *j*
UC	Upper difference in constant coefficients between drawpoint *i* and *j*
LC	Lower difference in constant coefficients between drawpoint *i* and *j*
H_i	Height of draw column *i* after extraction according to angle of draw □

3.1. Objective function

The objective function is to generate a schedule to provide the sequence of drawing from drawpoints over the scheduling periods. It means selecting which drawpoint should be started, activated, and depleted in every period and, finally, closed.

Mine plans are optimized by using many criteria, such as profit, life of mine, mining costs, confidence level, and mineral resources, while attending to constraints related to production rates, plant capacities, and grades. Some companies focus on reducing production costs by maximizing reserves and throughputs in their projects; others try to optimize specific economic indicators such as NPV, the internal rate of return (IRR), the payback period (PB), or the profit investment ratio (PIR) [23, 26, 27].

The maximization of NPV is closely associated with maximizing ore tonnes, as the ore tonnes generate revenue [28]. The NPV approach recognizes the time value of money and represents the sum of the discounted value of future cash flows [29]. Generally in planning, the NPV is maximized because it will yield the maximum profit to the mining companies. Several operations have recognized this strategy as the main driver for the mine planning process [17]. The production rate corresponding to the maximum NPV is the optimum production rate [30].

In this paper, the goal of all models is to maximize the NPV of the block-caving projects over the life of a mine in a time-dynamic manner, while satisfying all draw control system constraints and other operational constraints. The MILP objective function, equation (1), is composed of the economic value of the draw column and a continuous decision variable $X_{i,t}$, which indicates the portion of a draw column which is extracted in each period.

$$Max\sum_{i=1}^{I}\sum_{t=1}^{T}\left[\frac{Value_i}{(1+dsc)^t}\right]X_{i,t} \tag{1}$$

3.2. Constraints

Operational and technical constraints of block-cave mining operations are considered to control the outputs of the optimizations model. Number of decision variables depends on the number of drawpoints and the number of slices in each drawpoint.

One of the main goals of long-term mine planning is to integrate internal and external mine planning factors that affect the performance of the mine operation. At the same time, long-term planning is responsible for coordinating strategic goals and operational activities [31]. Getting the best solution requires using an operations research technique to limit the objective function by some constraints. These constraints appear in several different forms: geotechnical, grades, period, advancement direction, and priority of productive units, productivity, production rates, and many others that depend on the mining method. The construction of the optimization problems has required rational studies of which mining constraints are applicable in each case [32]. The constraints considered in the integer program are generally quality and quantity requirements. Knowledge, experiments of mine planners, and corresponding planning horizons have a critical role in the process of assigning constraints to the optimization problems. The following constraints are part of the problem in deriving the formulation:

3.2.1. Mining capacity

Equation (2) and (3) ensure that the total tonnage of material extracted from drawpoints in each period is within the acceptable range that allows flexibility for potential operational variations.

$$\sum_{i=1}^{I}(Ton_i)\times X_{i,t} \le MC_u \tag{2}$$

$$\sum_{i=1}^{I}(Ton_i)\times X_{i,t} \ge MC_b \tag{3}$$

3.2.2. Production grade

Equations (4) and (5) force the mining system to achieve the desired grade. The average grade of the element of interest has to be within the acceptable range and between certain values.

$$\sum_{i=1}^{I} Ton_i \times X_{i,t} \times (gr_{l,i,t} - \widetilde{gr_{i,t}}) \le 0 \tag{4}$$

$$\sum_{i=1}^{I} Ton_i \times X_{i,t} \times (\widetilde{gr_{i,t}} - gr_{u,i,t}) \le 0 \tag{5}$$

3.2.3. Maximum number of active drawpoints

According to equations (6), (7), and (8) in each period, the number of active drawpoints must not exceed the allowable number and has to be constrained according to the size of the ore-body and the available infrastructure and equipment. A large number of active drawpoints might lead to serious operational problems.

$$E_{i,t} - \frac{Ton_i}{DR_{l,i,t}} \times X_{i,t} \le 0 \tag{6}$$

$$X_{i,t} - E_{i,t} \le 0 \tag{7}$$

$$\sum_{i=1}^{I} E_{i,t} \le Num_{E_{i,t}} \tag{8}$$

3.2.4. Precedence of drawpoints

The precedence between drawpoints is controlled in a horizontal direction. Controlling the order of extraction of drawpoints through an advancement direction is the goal of the precedence constraint. According to the advancement direction, for each drawpoint *i* there is a set A^i which defines the predecessor drawpoints among adjacent drawpoints that must be started before drawpoint *i* is extracted. Equation (9) controls the precedence of extraction.

$$S_{i,t} - \sum_{j=1}^{t} S_{l,j} \le 0 \tag{9}$$

3.2.5. Continuous extraction

Equations (10) and (11) force the mining system to extract material from drawpoints continuously after opening until closing. Equation (12) is only used for period 1.

$$\sum_{t=1}^{T} S_{i,t} = 1 \tag{10}$$

$$E_{i,t} - E_{i,(t-1)} - S_{i,t} \leq 0 \tag{11}$$

$$E_{i,1} - S_{i,1} = 0 \tag{12}$$

3.2.6. Number of new drawpoints

Based on the footprint geometry, the geotechnical behavior of the rock mass, and the existing infrastructure of the mine, the maximum feasible number of new drawpoints to be opened at any given time within the scheduled horizon must be defined on the basis of equations (13) and (14).

$$Num_{Nl,i,t} \leq \sum_{i=1}^{I} S_{i,t} \leq Num_{Nu,i,t} \tag{13}$$

$$\sum_{i=1}^{I} S_{i,1} \leq Num_{Ei,1} \tag{14}$$

3.2.7. Reserves

Equation (15) ensures that the sum of the fractions of the draw column that are extracted over the scheduling periods in maximum value is one, which means there is selective mining. For that reason, all the material in the draw column may not be extracted.

$$\sum_{t=1}^{T} X_{i,t} \leq 1 \tag{15}$$

3.2.8. Maximum activity life

The activity period of the drawpoint, in the context of draw control, is mainly concerned with the assessment of draw rates to adjust extraction tonnage of any drawpoint and prevent any recompaction or dilution in the activity life of drawpoints. Maximum activity life constraint causes the maximum activity life of any drawpoint to be limited to a deterministic value, so the draw rate of the drawpoint must be large enough to maximize the NPV and small enough to prevent over-dilution. Equation (16) indirectly affects the draw rate by controlling the number of activity periods of any drawpoint. So if the activity period has a large value, then the draw rate can have smaller values, and increasing the drawpoint activity life increases the probability of recompaction and dilution.

$$\sum_{t=1}^{T} E_{i,t} \leq Act_{life} \tag{16}$$

3.2.9. Draw rate constraint

The development of an overlap and disjunctive (OD) system for regulating drawpoint production begins by breaking the production profile into a number of regions, each of which has a binary indicator variable. When the binary variable for each level takes a value of zero the draw constraint for that level is relaxed;

otherwise that region binds production. The OD system determines which region is active. In the first step of the proposed OD system, the line equation for each region is written. For this purpose, as shown in Figure 2, the general equation for the ramp-up region is written based on the depletion and the draw rate (see equation (17)).

$$(DR_{i,(t+m)} - DR_{l,i,t}) = \frac{(DR_{u,i,t} - DR_{l,i,t})}{M - X_t} \times (X_{i,(t+m)} - X_{i,t}) \qquad (17)$$

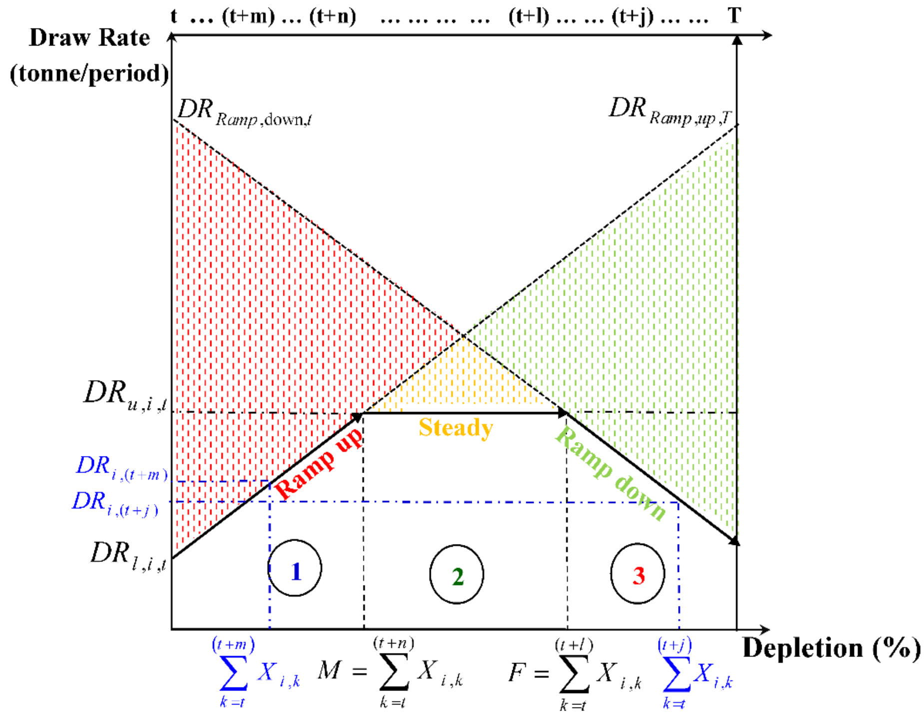

Figure 2. Ramp-up-steady-ramp-down situation

In the simple form it can be written that (see equation (18))

$$X_{i,(t+m)} = \sum_{t=1}^{t+m} X_{i,t} \qquad (18)$$

$$DR_{i,(t+m)} = X_{i,(t+m)} \times Ton_i \qquad (19)$$

Equation (20) shows the mathematical structure for the area under the ramp-up region.

$$X_{i,(t+m)} \times Ton_i - \left(\frac{(DR_{Ramp,up,T} - DR_{l,i,t})}{1 - \frac{DR_{l,i,t}}{Ton_i}}\right) \times \sum_{t=1}^{t+m} X_{i,(t+m)} \le DR_{l,i,t} - \left(\frac{(DR_{Ramp,up,T} - DR_{l,i,t})}{1 - \frac{DR_{l,i,t}}{Ton_i}}\right) \times \frac{DR_{l,i,t}}{Ton_i} \qquad (20)$$

With a similar process, the equations for the steady and ramp-down regions can be written as follows. Equations (21) and (22) are related to the steady and ramp-down regions respectively:

$$X_{Steady,T} \times Ton_i \le DR_{u,i,t} \qquad (21)$$

$$X_{i,(t+m)} \times Ton_i + (\frac{(DR_{Ramp,down,T} - DR_{l,i,t})}{1 - \frac{DR_{l,i,t}}{Ton_i}}) \times \sum_{t=1}^{t+m} X_{i,(t+m)} \leq DR_{Ramp,down,T} + \frac{(DR_{Ramp,down,T} - DR_{l,i,t})}{1 - \frac{DR_{l,i,t}}{Ton_i}} \times \frac{DR_{l,i,t}}{Ton_i} \quad (22)$$

Based on equations (20), (21), and (22), the problem can be formulated for the required PRC. In each period that drawpoint depletion is started, the draw rate must be equal to the minimum acceptable draw rate. Equation (23) forces models to start depletion with a minimum acceptable draw rate.

$$DR_{l,i,t} \times S_{i,t} - Ton_i \times X_{i,t} \leq 0 \quad (23)$$

3.2.10. Conditional draw rate constraint (CDR)

The presented conditional draw rate constraints in this paper seek to control undesirable problems among the draw columns according to special characters and geotechnical rules of any caving mine. The conditional draw rate (CDR) constraint is a fundamental part of schedule planning to ensure that an even draw is maintained across the cave.

There should be a close relationship between the depletion of a given production drawpoint and its adjacent drawpoints in all activated area. If the production difference between adjacent drawpoints is too much, material from a draw column with higher tonnage moves to the draw column with lower tonnage. The draw strategy of each drawpoint should not only be connected to the PRC, but should take into account the amount of the extracted material from the adjacent drawpoints during the periods in which the drawpoint is active. Therefore, to optimize draw control in block-cave production scheduling, two fundamental factors must be considered: (i) the draw rate of the drawpoint, and (ii) the conditional draw rate between the drawpoint and its adjacent drawpoints. These two factors result in a uniform extraction across the cave. The CDR constraint includes two components: upper and lower difference tonnage coefficients (UT and LT), and upper and lower difference constant coefficients (UC and LC).

- *Difference tonnage coefficients (DTC)*

The UT and LT difference tonnage coefficients of CDR are defined based on the angle of the draw in the advancement direction. The angle of the draw controls the tonnage of extraction from adjacent drawpoints. The angle of the draw can be steep or shallow and is defined by the operation's production rate, stress distribution in the rock mass, strength of the host rock, cave stability, engineering judgment, and practical strategies from other projects. It is important to maintain the determined angle of the draw during the mine life and to prevent sudden changes of the angle of the draw between periods. A significant variation in the depletion rate among the draw columns in the advancement direction leads to an increased amount of chaotic movement within the broken rock. Stress is then redistributed throughout the mining area as a function of the depletion rate in all drawpoints. Also, dilution which is the result of mixing of fragmented material along the draw column and uneven draw among the draw columns seriously increases. Whenever the angle of draw is tightened, the adjacent drawpoints are required to have a closer production rate (Figure 3). The UT and LT of drawpoint *i* and *j* are calculated by equation (24).

$$DTC = \frac{\pi}{4} \times DC^2 \times \rho_j \times \tan\beta \times \sqrt{(\mathrm{X_i} - \mathrm{X_j})^2 + (\mathrm{Y_i} - \mathrm{Y}_j)^2} \quad \begin{cases} \text{For } UT & \beta = \beta_{\max} \\ \text{For } \mathrm{L}T & \beta = \beta_{\min} \end{cases} \quad (24)$$

The aim of the CDRAT constraint is to control the total difference in depletion rates of adjacent drawpoints along the advancement direction in period *t*. If the adjacent drawpoints are still mining at low waste contents, it may be necessary to continue to extract ore from the high waste drawpoints to maintain the correct shape to maximize the extraction from the more economic drawpoints [33]. The difference in draw tonnage between adjacent drawpoints is restricted by the CDRAT constraint. This constraint ensures that

(i) the dilution is controlled and (ii) over- or under-depletion does not occur. This prevents damage to the extraction level and other mine structures that can result from induced stresses.

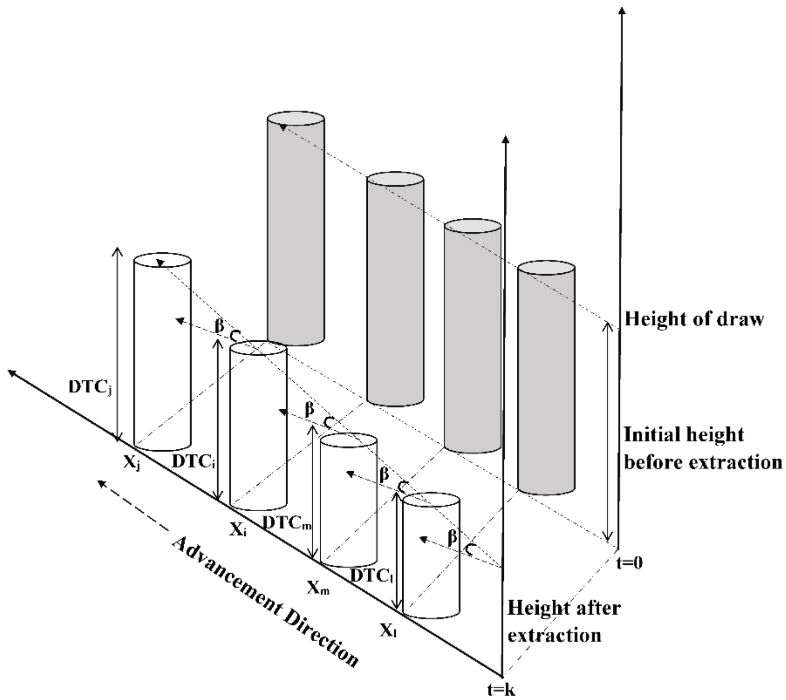

Figure 3. Influence of angle of draw on adjacent drawpoints

Equation (25) shows the mathematical structure of the CDRAT constraint:

$$LT_j \times DR_{i,t} + MinDR_{j,t} \times (1-E_{i,t}) \leq DR_{j,t} \leq UT_j \times DR_{i,t} + MaxDR_{j,t} \times (1-E_{i,t}) \tag{25}$$

The draw rate is a function of the draw column's tonnage and the portion of extraction in each period (see equation (26))

$$LT_j \times X_{i,t} \times Ton_i + MinDR_{j,t} \times (1-E_{i,t}) \leq X_{j,t} \times Ton_j \leq UT_j \times X_{i,t} \times Ton_i + MaxDR_{j,t} \times (1-E_{i,t}) \tag{26}$$

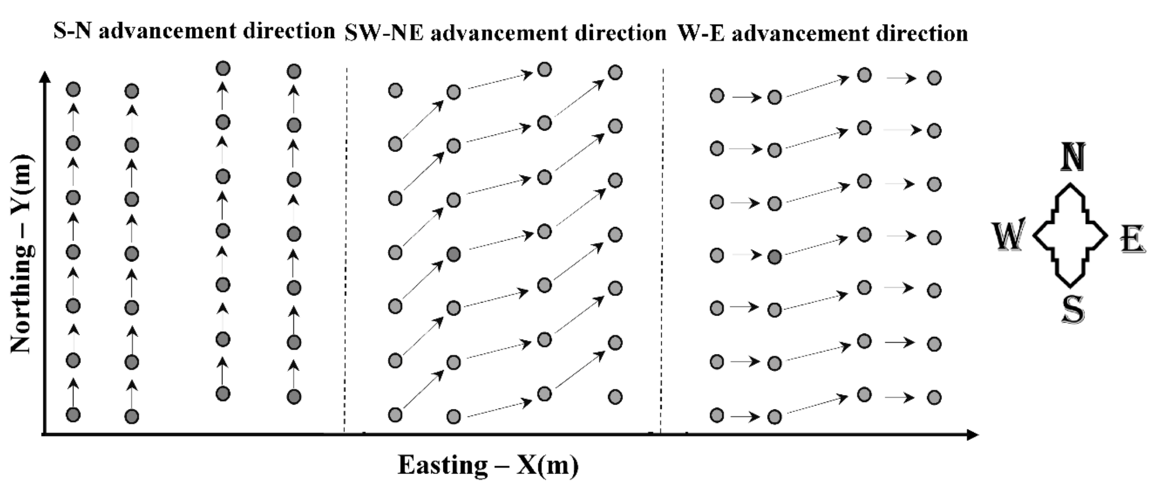

Figure 4. One adjacent drawpoint for any drawpoint in different advancement directions

- *The conditional draw rate of the a drawpoint and its adjacent drawpoints based on the advancement direction at period t (CDRMT)*

This section investigates the effect of the adjacent drawpoints on the depletion rate from a drawpoint in the advancement direction.

Increasing the distance from the considered drawpoint reduces the influence of adjacent drawpoints. It is necessary to define a radius to determine the number and location of adjacent drawpoints. This radius is defined in a way that all drawpoints available in this area have a direct effect on the considered drawpoint. Figure 5 shows the search radius and adjacent drawpoints of the considered drawpoint in different advancement directions.

Equation **Error! Reference source not found.** controls the CDRMT constraint.

$$LT_j \times X_{i,t} \times Ton_i + MinDR_{j,t} \times (1-E_{i,t}) \le X_{j,t} \times Ton_j \le UT_j \times X_{i,t} \times Ton_i + MaxDR_{j,t} \times (1-E_{i,t})$$
$$\text{j}: 1,2,3,... \in R^i \tag{27}$$

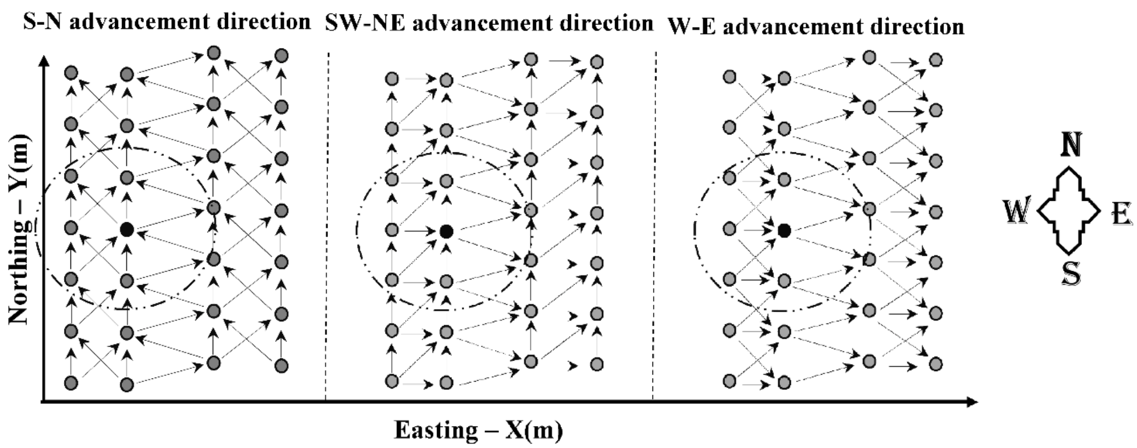

Figure 5. Multi-neighboring of any drawpoints in different advancement directions

- *Conditional draw rate constraint by period t (CDRB)*

Draw column height is the height of ore above the drawpoint with an acceptable height of dilution that can be drawn from the drawpoint [12]. The main parameter to simulate the mixing process is the height of the interaction zone. The greater the height of interaction, the sooner the dilution will appear in the drawpoint. The CDRB reduces the total difference of depleted tonnage between adjacent drawpoints (*i* and *j*) by period *t*. The total difference in tonnage between adjacent drawpoints (*i* and *j*) before the extraction has a constant value (CV). After starting the depletion from drawpoints *i* and *j* the remaining material in the draw columns can vary and have any tonnage. So the drawn surface can be uneven if the difference in depleted tonnage cannot be controlled in drawpoints *i* and *j*. Equation (27) defines the condition that seeks to limit the total difference in any adjacent drawpoints' depletion tonnage to a given value such as CV (see Figure 6). However, the CDRB controls the summation of the total difference in depleted tonnage from drawpoints *i* and *j* in each period and additionally, from the starting period to the considered period. It is important to note that, the primary objective of the conditional draw rate constraint in period *t* is to regulate block-cave production to conform to the complete drawn program.

$$\left[Ton_i - Ton_j + Ton_j(1-S_{j,t})\right] \times LC \le \sum_{t=1}^{T} DR_{i,t} - \sum_{t=1}^{T} DR_{j,t} \le \left[Ton_i - Ton_j + Ton_j(1-S_{j,t})\right] \times UC \tag{27}$$

Equation (28) shows the CDRB constraint based on extracted tonnage by period *t*:

$$\left[Ton_i - Ton_j \times S_{j,t})\right] \times LC \le (Ton_i \times \sum_{t=1}^{T} X_{i,t} - Ton_j \times \sum_{t=1}^{T} X_{j,t}) \le \left[Ton_i - Ton_j \times S_{j,t})\right] \times UC \tag{28}$$

LC and UC are the minimum and maximum values of CV. Rules of thumb, feedback from the rock mechanics and mine stability experts, and practical strategies from previous extractions can define CV.

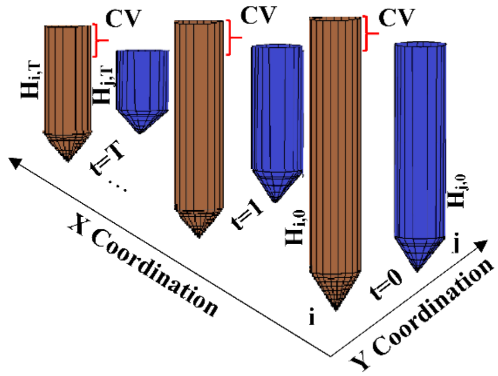

Figure 6. Draw column height in all periods

4. Solving the optimization problem

In this paper, the presented MILP models were developed in MATLAB [34] and solved in the IBM ILOG CPLEX [35] environment. CPLEX uses a branch-and-bound algorithm to solve the MILP model, assuring an optimal solution if the algorithm is run to completion. A gap tolerance (EPGAP) of 9% is used as an optimization termination criterion. This is an absolute tolerance between the gap of the best integer objective and the objective of the remained best node.

5. Case study

The production schedule of 325 draw columns over 15 periods for each draw rate strategy is investigated. Figure 7 shows the drawpoints' herringbone layout. The total tonnage of material is 38.71 (Mt) with an average density of 2.7 (t/m^3) and an average grade of 0.41% Cu. Figure 8 illustrate the tonnage and grade distribution of the draw columns. The searching radius in the CDRMT constraint is 20 m. UC and LC in the CDRB constraint are 0.25 and 3, respectively. The performance of the proposed MILP models was analyzed based on maximizing the NPV at a discount rate of 12%. The draw control system, by enrolling an exact production rate curve and conditional draw rate constraints, seeks to optimize and present practical block-cave planning.

The models were tested on a Dell Precision T7600 computer with Intel(R) Xeon(R) at 2.3 GHz, with 32 64 GB of RAM. In all models, as part of their implementation, the maximum depletion of the draw column from ramp up to steady (M) is assumed to be 30%, the maximum depletion of the draw column from steady to the ramp-down region is assumed to be 90%. The other scheduling parameters have been summarized in Table 2. The models are verified in the south to north (SN) advancement direction. This advancement direction was selected using the methodology developed by Khodayari and Pourrahimian [36]. Khodayari showed that the cumulative economic value of all drawpoints can be used to determine the best advancement direction to maximize the NPV. Figure 9 shows the results of the model for 325 drawpoints. As shown, the best direction is SN.

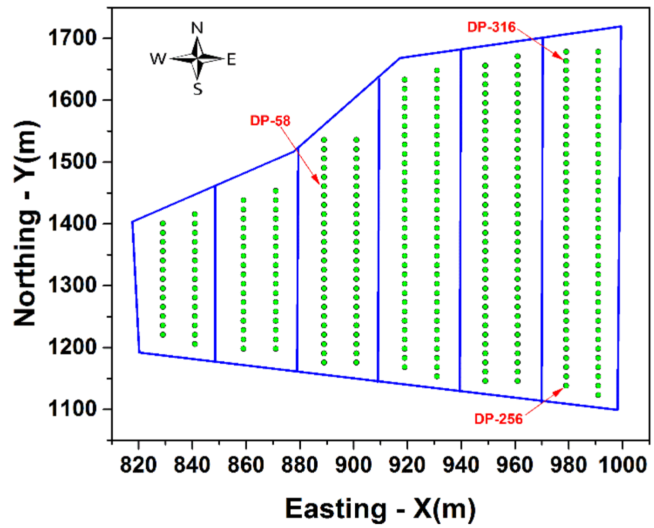

Figure 7. Drawpoints' herringbone layout

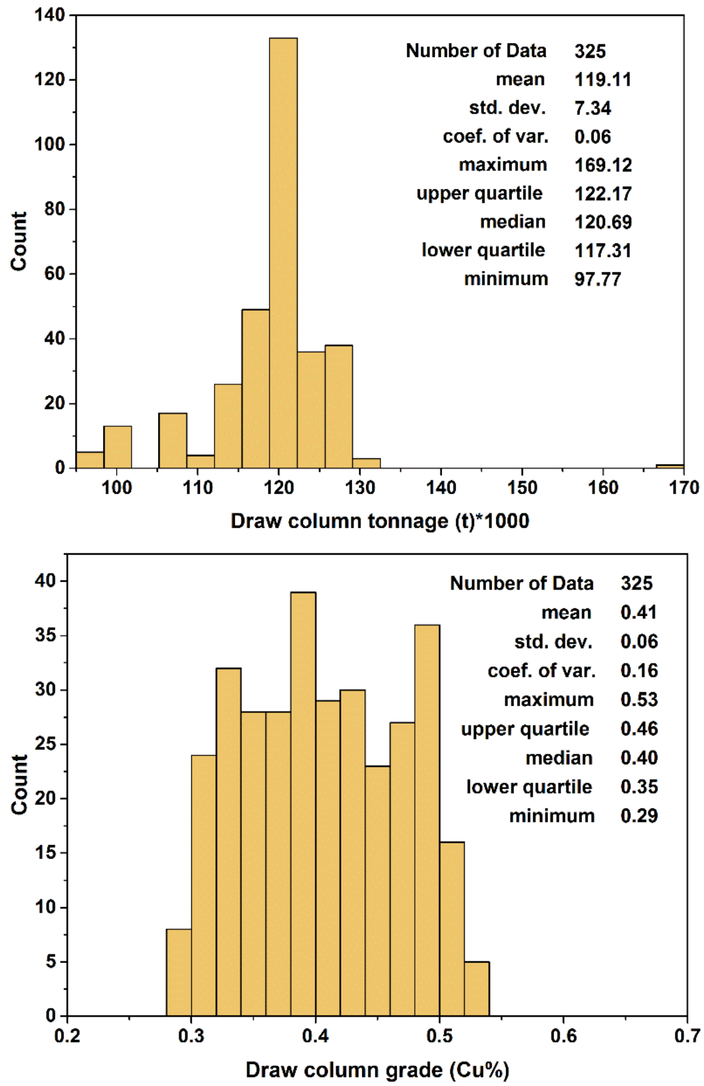

Figure 8. Grade and tonnage distribution for 325 draw columns

The problem was solved in the SN direction for four resolutions: draw rate (DR), CDRAT, CDRMT, and CDRB. Table 3 `shows the results of the all models. The DR model is considered a basic model because it has all of the other models' details. The obtained NPV from the DR is $451.07M with the optimality gap of 9%.

Table 2. Production scheduling parameters

Parameters		Value
Number of periods		15
Maximum number of activity year of drawpoints		4
Draw rate (kt/year)	Min	11
	Max	40
	M (%)	30
	F (%)	90
Angle of draw (°)	β max for UT	15
	β min for LT	5
Number of new drawpoints per year	Max	50
	Min	3
Average grade of production (%)	Max	0.6
	Min	0.4
Number of maximum active drawpoints per year		90

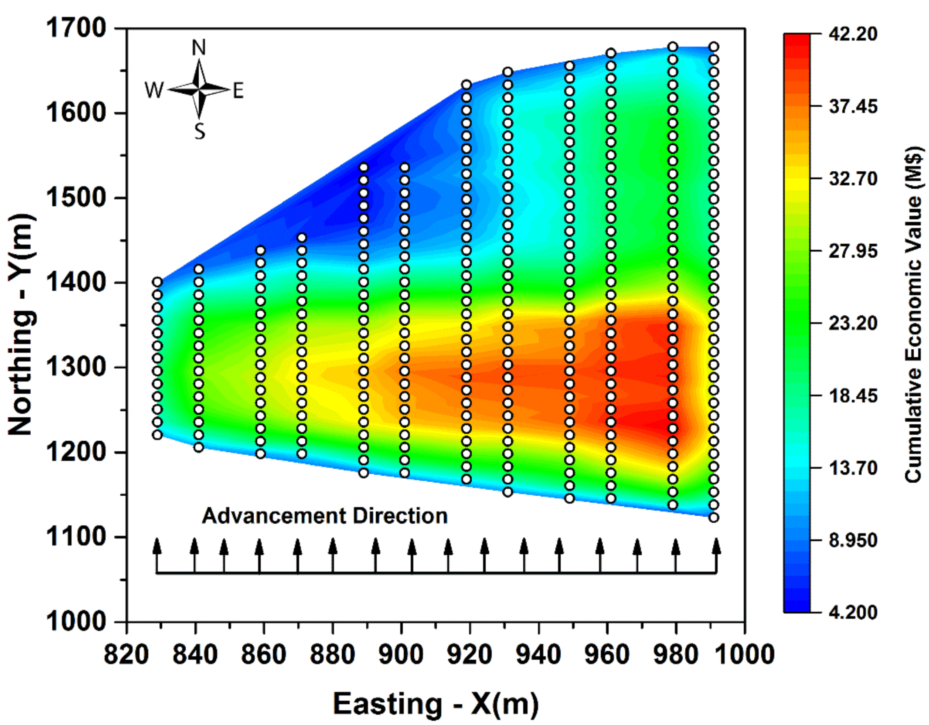

Figure 9. Mining advancement direction

Table 3. Numerical results for all models

Resolution	CPU time	Extraction (Mt)	Extraction (%)	NPV (M$)	Constraint number	Variable number	
						Con.	Bin.
DR	02:08:30	30.56	79	451.07	53650	4875	9750
CDRAT	11:20:43	30.97	80	436.66	53650	4875	9750
CDRMT	10:42:40	28.91	75	424.37	53650	4875	9750
CDRB	07:07:42	32.51	84	445.07	58525	4875	9750

The maximum obtained NPV from all four models belongs to DR model. The total running time in this resolution is 02:08:30. This time, according to the complex structure of the DR model, is desirable. The total extracted tonnage from all drawpoints in this resolution is 30.56Mt. This means that about 79% of all material is extracted in this model. The value of the NPV for the CDRMT resolution is lower than other resolutions and the tonnage of the material that can be depleted from the active drawpoints in this model is less than that of other models. The difference between the obtained NPV of the DR and CDRMT models is less than 6.3%. The minimum percentage of extracted material belongs to CDRMT model. The difference in extracted materials in both models is less than 5.07%. Thus, CDRMT model can simultaneously provide economic and geotechnical goals. Figure 10 shows the cash flow for different resolutions.

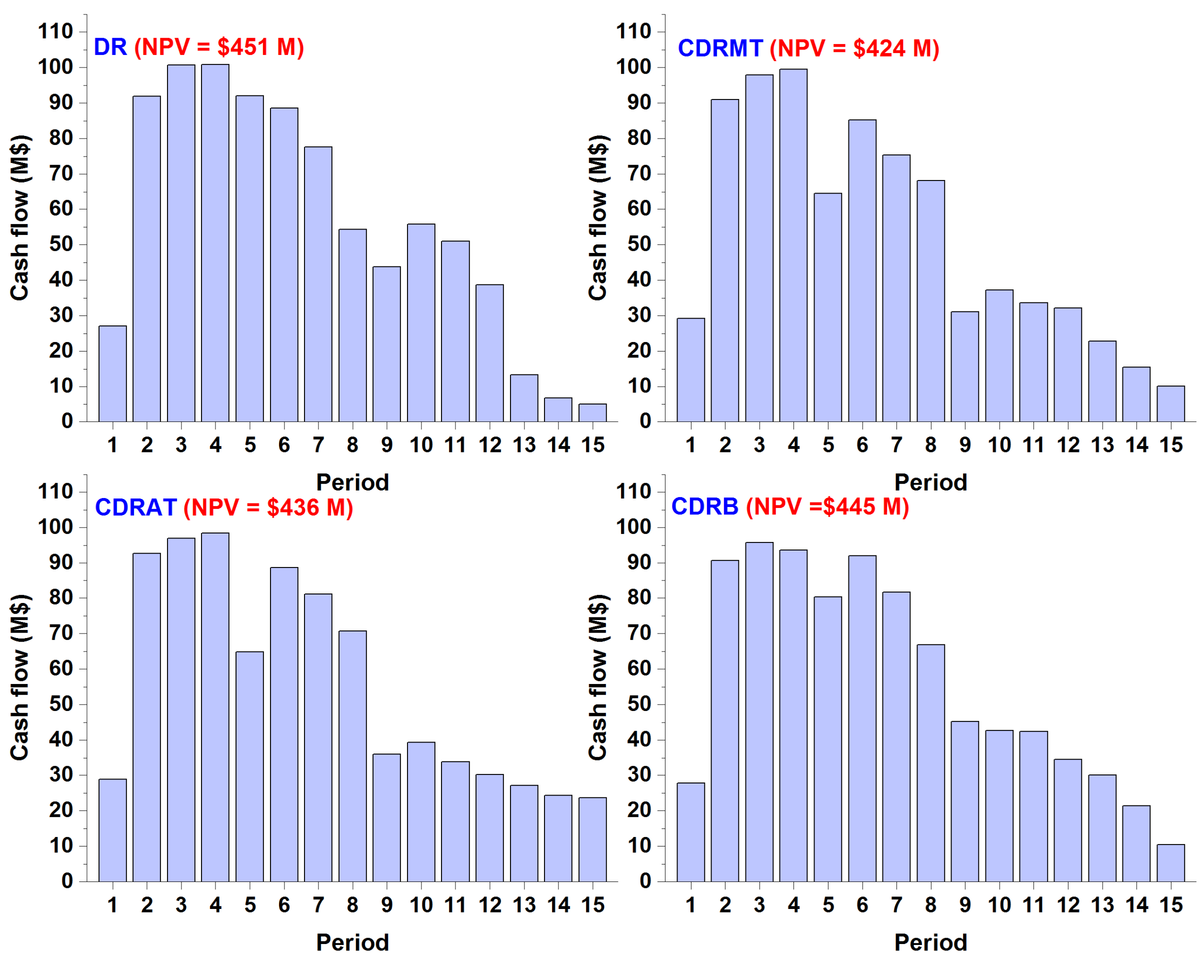

Figure 10. Comparison of cash flow for all resolutions

Figure 11 shows the production tonnage and the average grade of production in each period of all resolutions. In period 1 because of the minimum draw rate and total allowable active drawpoints, production is less than the maximum mining capacity. In the CDRAT model, after period 1, the tolerance of production tonnage is less than other models. Therefore, the CDRAT model seeks to evenly extract materials from drawpoints during the life of the mine. After period 11, the production tonnage decreases gradually in all of the models. The average grade of production increases gradually from periods 1 to 5 and after period 5 it shows a descending trend until the end of the mine life for all resolutions. During the last periods, because of reaching the top of the draw column and increasing the probability of dilution, the average grade of production is less than early years. It should also be noted that dilution is reduced because of the controlling feature of the production rate curve in the draw control system.

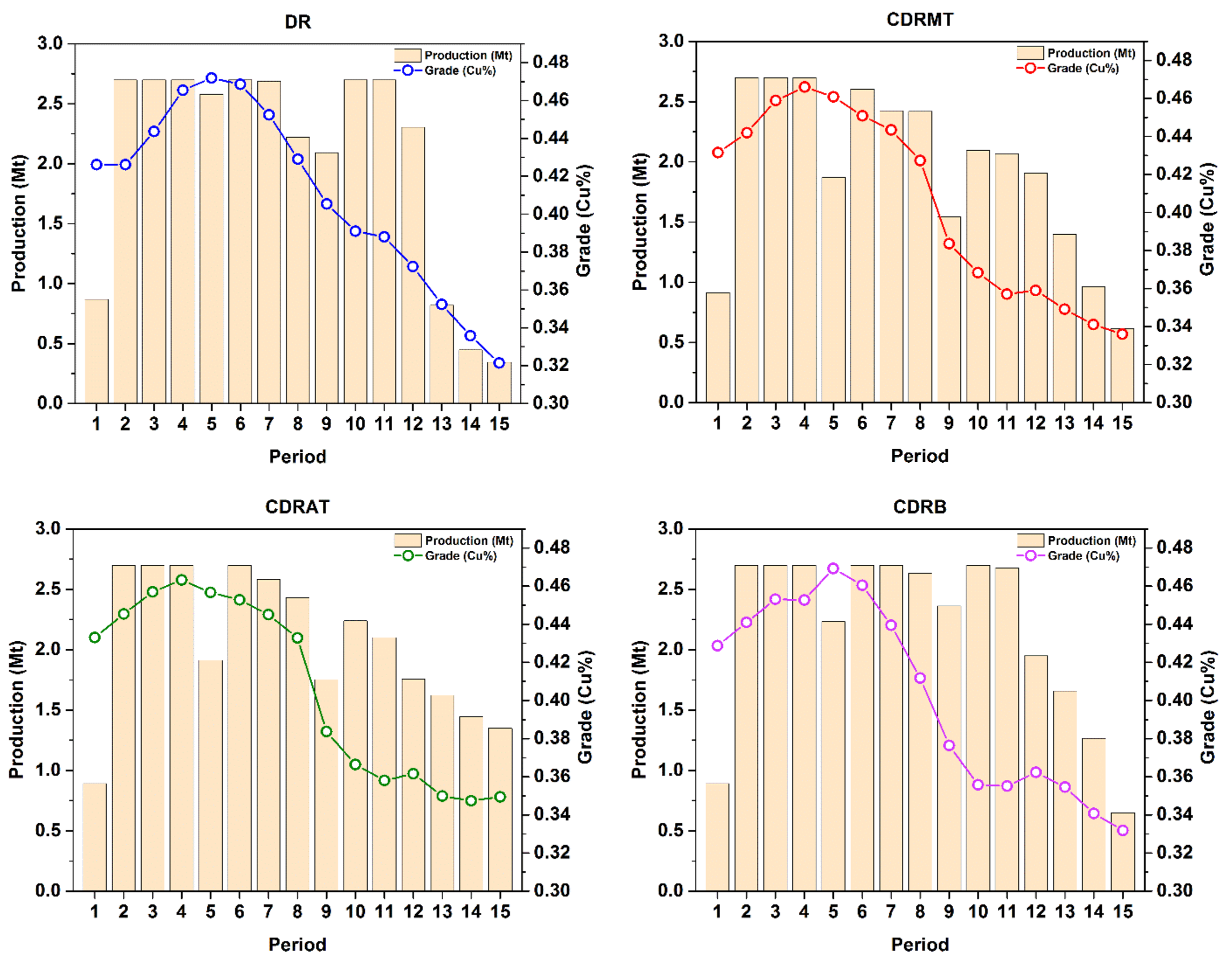

Figure 11. Production tonnage during the mine life for all resolutions

Figure 12 shows the maximum number of active drawpoints in each period for all models. The maximum number of active drawpoints in all periods is less than 90. The number of active drawpoints in the CDRAT, CDRMT, and CDRB models in the last periods is more than the number in the DR model. In the CDRAT model, the difference between the number of active drawpoints in the first and last periods is less than that in other models. The conditional draw rate models seek to deplete draw columns evenly by keeping the same number of active drawpoints in different periods.

According to the defined PRC, drawpoints cannot be depleted arbitrarily. On the other hand, the material with a lower economic value and grade can remain in the number of drawpoints because of the defined objective function and the constraints. Figure 13 illustrates the draw rate changes for three different drawpoints in all models. It is clear that the defined PRC for the selected drawpoints is satisfied in all models. Extraction from drawpoint 256 (DP256) in the DR model is started in period 1 with the minimum acceptable draw rate (11 kt). Then it increases gradually to reach the maximum acceptable draw rate (40 kt) in period 3. The tonnage of extraction from drawpoints varies based on the drawpoints' economic values. The objective function maximizes the NPV and the tonnage of extraction from each draw column is the result of optimization.

The results show that all the defined constraints have been satisfied in all models. The draw rate amount for each drawpoint and starting and finishing periods are obtained as a result of optimization. The models extract the material from each draw column based on the defined draw rate model while maximizing the NPV of the operation.

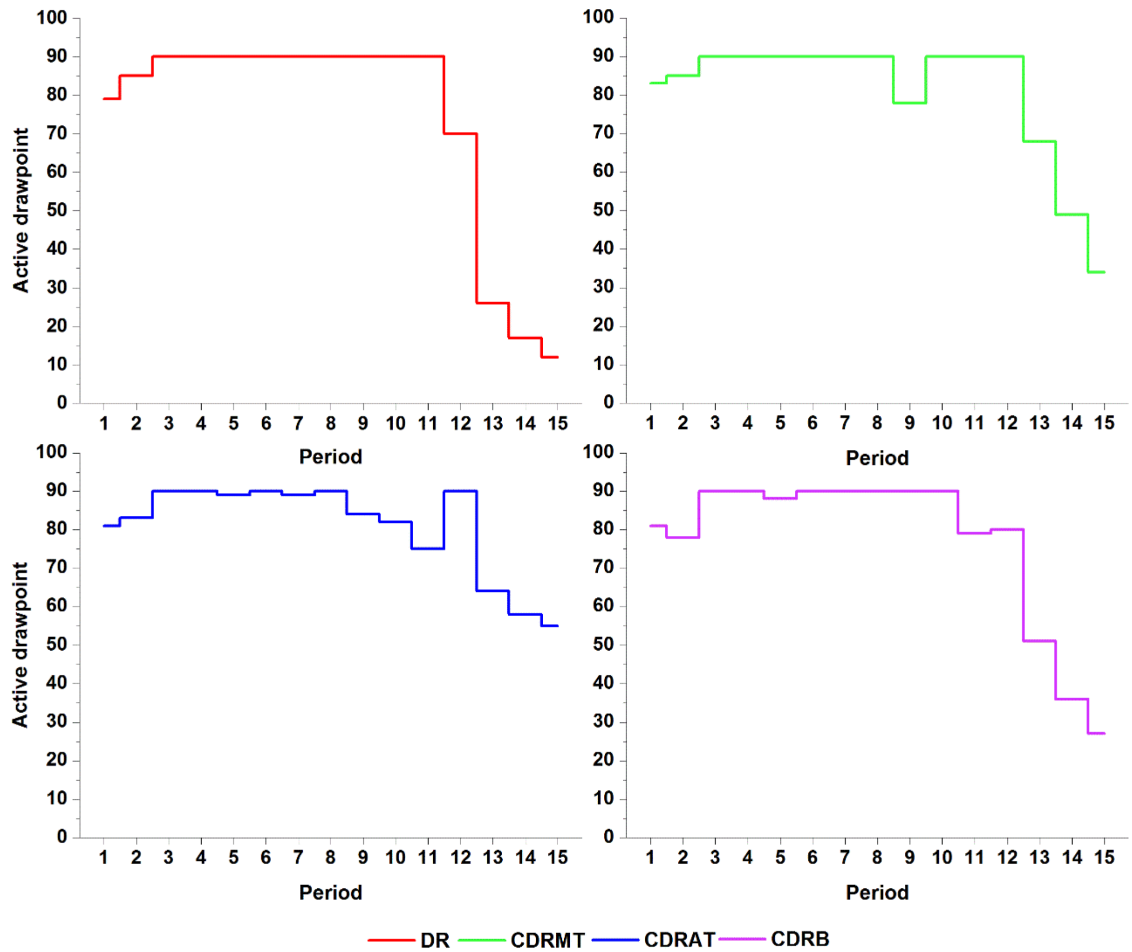

Figure 12. Number of active drawpoints in each period during the mine life

According to Figure 13, the drawpoints that started to deplete in the first periods are less influenced by CDR. The DP256 is one of the southern drawpoints which is started in period 1 in all resolutions. The DP58 has different start periods because it is almost at the end of the advancement direction. Different resolutions have different effects on the DP58. The maximum draw rate in all models is 40000 (tonne/year). The DR and CDRB models can reach the maximum draw rate of 40000 (tonne/year). In the CDRMT and CDRAT, the draw rates are influenced by the angle of draw. Therefore, the depletion rate, according to determined angles and the advancement direction, has a reduction trend. By reducing the draw rate, the CDRMT and CDRAT seek to increase the activity periods of drawpoints. In the CDRAT and CDRMT, all drawpoints are active in four periods but in other models the maximum activity life is less than four periods.

Figure 14 shows the height of the draw columns at the end of different periods for all resolutions. The defined advancement direction has also been satisfied. The height of the drawpoints represents the surface displacement at the end of each period. One of the advantages of the draw control system is that it controls surface displacement by using the draw rate in all drawpoints during the life of the mine. Whenever geotechnical constraints have tightened conditions, the overall displacement in the surface is controlled better. Figure 14**Error! Reference source not found.** shows that the extraction rate from the draw column in the CDRAT and CDRMT models follows an even pattern. Finally, the dilution in the last periods in the marginal draw column reduces because the CDR models restrict more depletion of material in those draw columns. Surface displacement is in the expected shape according to allowable depletions in all CDR resolutions compared to the DR model.

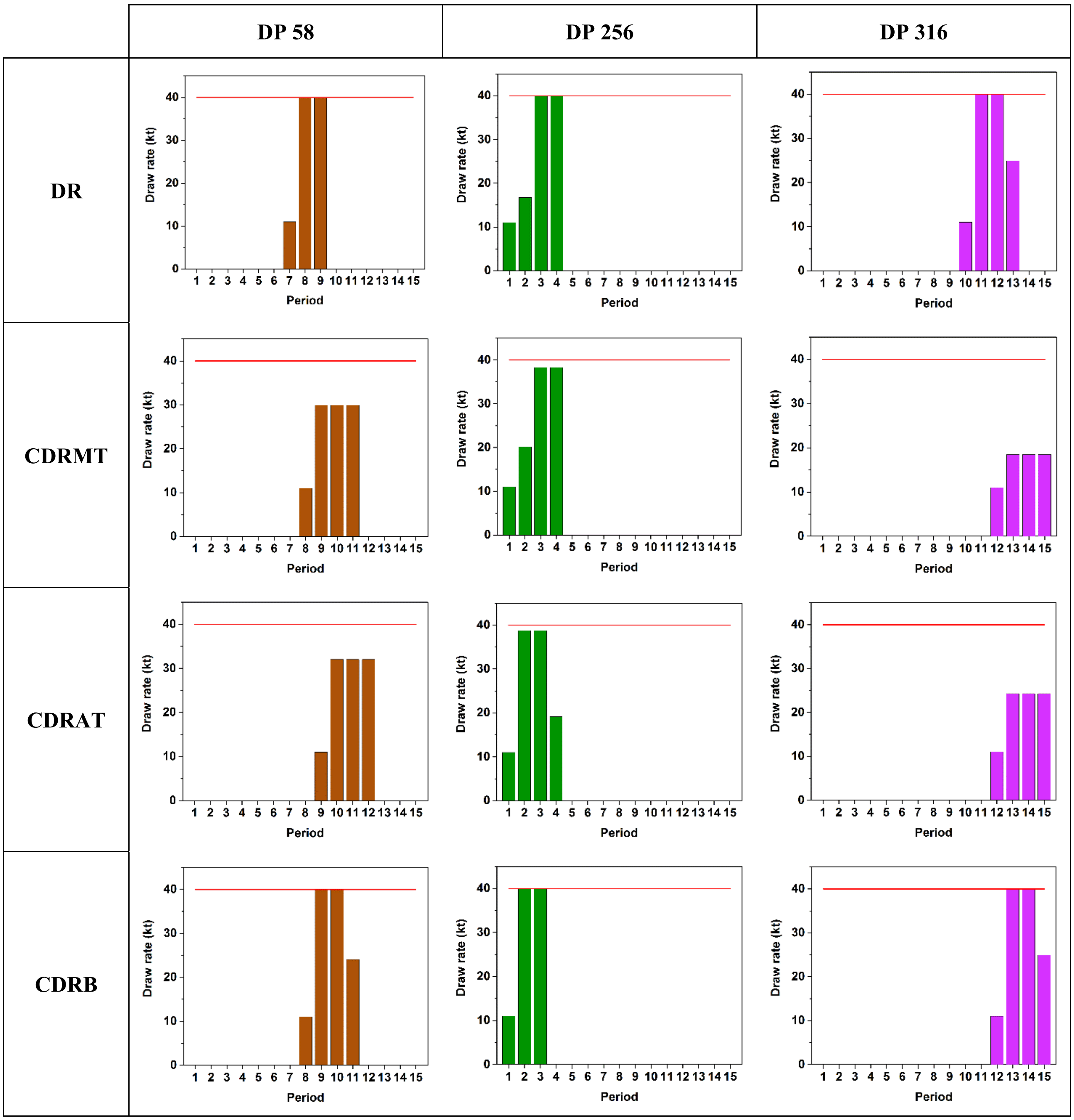

Figure 13. Obtained draw rate as result of optimization for different drawpoints in all models

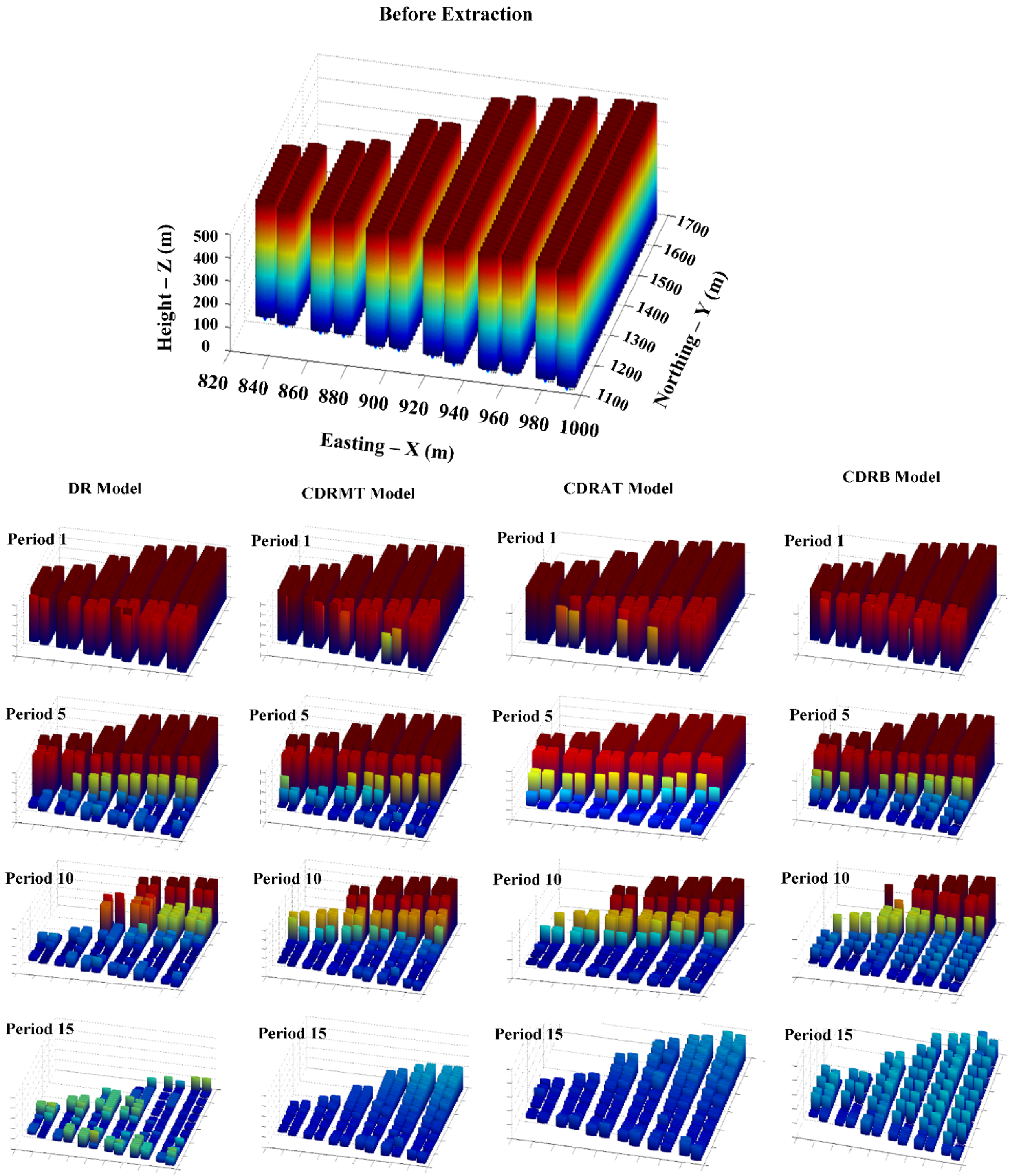

Figure 14. Height of drawpoints at the end of periods 1, 5, 10, and 15 for all resolutions

6. Conclusion

This paper presented a practical draw control system based on some conditional approaches to manage draw rates of block-cave operations. The presented model maximizes the NPV subject to all operational and geotechnical constraints. The MILP formulation for a block-cave production schedule was developed, implemented, and tested in the CPLEX/IBM environment. To manage drawpoint production, a draw rate constraint based on the PRC was established. Three different resolutions' responses to conditional constraints were added to the exact management system of PRC to control the depletion rate among all drawpoints in the caved area.

The draw control system was classified in four alternative resolutions to be modelled and practiced by all mines according to their draw requirements. Among these four resolutions, the depletion rate from the draw column in CDRAT and CDRMT models follows an even extraction pattern. The CDR models by controlling depletion rate among drawpoints, number of active drawpoints, and production grade during the mine life in compared to the DR model seek to deplete broken rock from the draw columns evenly. The CDRAT model depletes more evenly than all of the other models. Although the DR model reduces unfavorable displacement and dilution in block-cave mining, the CDR models work better and reduce unfavorable displacement more than the DR model. The CDR constraints increase the size of the model and solving time but the obtained NPVs are acceptable and the generated schedule is practical and realistic.

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Block-Cave Production Scheduling Using A Multi-Index Clustering Technique

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ABSTRACT

Rapid improvement in underground mining technologies causes some disturbs with accumulating huge amounts of the source, destination and extraction time of ore and waste during the life of mine. Long-term planning is one of the most important stages that determines the distribution of cash flows over the life of mine and can significantly impact the feasibility of the project. An optimal production schedule in block caving will not be practical unless the geotechnical constraints are considered. The draw control is one of the main aspects of geotechnical constraints in block-cave operation. Most of the mathematical draw control systems do not have an exact production rate curve to manage draw rates of the drawpoints. In addition, these systems are too complex to provide a practical solution for real block-cave mines. This paper presents a mixed-integer linear programming (MILP) model to optimize the extraction sequence of drawpoints over multiple time horizons of block cave mines with respect to the draw control systems. Also, a multi-index clustering algorithm is presented to reduce the size of the large-scale MILP model to be able to solve the problem in a reasonable time. The results show a significant reduction in the size of the MILP model and CPU time. Application and comparison of the production schedule based on the draw control system with the clustering technique is presented using 2,487 drawpoints to be extracted in 32 years.

1. Introduction

Block and panel caving have become the underground bulk mining methods of choice and expected to continue in the future [1]. Block caving is a complex and large-scale mining method. The application of block caving is for low-grade, caveable, and massive ore-bodies. Block cave mines demand a large capital investment for the development and construction of any production units. Planning of block-caving operations poses complexities in different areas. Generating a production schedule is one of these areas and has involved lots of responsiveness from the researchers during the past decades. Mine planning consists of defining the source, destination and extraction time of ore and waste during the life of mine. Production scheduling of any mining system has an enormous effect on the operation's economics. Nowadays, production scheduling is one of the key components in determining mine viability, because the mining industry faces lower grade and marginal reserves. In block caving projects, deviations from optimal mine plans may result in significant financial losses, future financial liabilities, resource sterilization, unbalanced cave subsidence, the flow of muck, and infrastructure instability.

A major aspect of mine planning is the optimization of long-term production scheduling. The aim of long-term production scheduling is to determine the time and sequence of extraction and displacement of ore and waste in order to maximize the overall discounted net revenue from a mine within the existing economic, technical and environmental constraints [2]. Thus, mining engineers are tasked to design and

A version of this paper has been submitted for publication in International Journal of Mining Science and Technology (IJMST).

optimize the resource recovery to ensure the maximum return on investment whilst still tempered by practical mining and geotechnical constraints [3].

The ore extraction rate and the incorporation of new areas are key operational parameters in block caving. They both control the cave back geometry which is mostly responsible for the induced stress state around productive levels [4]. Rubio [5] pointed out that block caving requires more detailed geotechnical investigations of the ore-body compare to other methods in which conventional drilling and blasting are employed as part of the mine production. Apprehending different operational and geotechnical situations is fundamental to preform and control caving. Geotechnical condition in the form of an exact production rate curve (PRC) controls the draw system. Caveability, in the context of draw control, is primarily concerned with balancing caving rates and production. The draw rate is technically related to the potential seismic activities and geotechnical hazards in caving [6].

Draw control is the bridge which connects production schedule and geomechanic features of the caving operations [7].

A strict planning system depends upon the production control and the ability to implement an effective draw strategy over the life of mine. Introducing an optimum draw control system based on mathematical programming that integrates system's constraints such as economic, environmental, operational, metallurgical, and geological, could result in a successful planning tool to be used by the mining industry. In this paper, a mixed-integer linear programming (MILP) formulation is developed to generate a realistic and practical production schedule. Presented MILP should not over- or under-estimate the value of the operation and have to solve models in a reasonable CPU time for a large-scale block-cave operation. It is intended to help companies to maximize economic outcomes with respect to geotechnical production rate curves. Such a model, which intends to work for real world conditions, must respond to all practical problems which might happen during extraction. This means that numerous constraints must be built into the model; consequently, the size of the MILP model increases substantially. The model must accommodate several decision variables over the life of mine. Solving large-scale problems is a challenge, it could be impossible to find the optimum solution or the solution time is not reasonable. Therefore, it is crucial to reduce the size of the problem using techniques in which the shrunk model can guarantee solution values with minimum deviations from the original model. As a result, this paper outlines an investigation into the application of the hierarchical clustering method for such oversized MILP model. The efficiency of the proposed algorithm is evaluated through a life of mine production scheduling case study with 2,487 drawpoints.

2. Literature review

This section has focused on the mathematical programming application in block-cave mining, and aggregation or clustering techniques for underground mining (notably block-cave projects). Some optimization models exist for production scheduling in block-cave mining, but the literature on draw rates, which is based on the PRC, is relatively new.

Chanda [8] used MIP for combining simulation to production scheduling in a block-caving operation. He concentrated on a short-term planning problem that covers a time horizon of few weeks to few months, applying single step optimization rather than multi-period optimization. This model did consider geometric constraints between drawpoints. Early models did not incorporate the variability and the dynamic behavior of the fundamental models throughout the mine and did not integrate the operational upsets that affect productivity because of lack of draw control planning constraint in models.

Rubio and Diering [9] noted that Chanda has not recognized the fact that the set of constraints is a function of the defined planning horizon. Guest et al. [10] assumed that by following a set of surfaces that conceptually define a draw control strategy, dilution can be minimized and therefore the net present value can be maximized. It should be noted that they stated the importance of the draw strategy on dilution control as part of the production scheduling process.

Rahal et al. [11] reviewed state-of-the-art in production schedule optimization and compared the complications related to caving. They noted that none of the available scheduling methodologies fully address complications associated with caving, in particular ore mixing and frequent loss of drawpoints. Additionally, Rahal [12] used a mixed-integer linear goal programming (MILGP) model in which the model had dual objectives of minimizing the sum of the production and external sources depletion simultaneously. This algorithm assumes that the optimal draw strategy is known. He developed life-of-mine draw profiles for estimated scenarios and showed that by using the results from their integer program, they greatly reduced deviation from ideal drawpoint depletion rates while adhering to a production target. Rahal considered the following constraints in his model: capacity, precedence, material handling, and maximum and minimum levels of draw rates. Rahal emphasized that the major outcomes from his research were a preliminary optimized life-of-mine production plan and the identification of areas where additional work can refine the parameters which were used in the optimization.

Diering [13] presented a non-linear programming optimization method to maximize NPV and minimize the deviation between a current draw profile and the target defined by the mine planner. Diering emphasizes that this algorithm could also be used to link the short-term with the long-term plan. The long-term plan is represented by a set of surfaces used as a target to be achieved based on the current extraction profile when running the short-term plans. Diering used only two boundaries for the draw rate constraint in the mathematical model.

Smoljanovic et al. [14] presented an MILP model to optimize the NPV in a panel cave mine to study the drawpoints' opening sequence. Their emphasis was in the precedence, geometrical, and production constraints. This model was a good starting point for panel or block caving, but the precedence and capacities constraints should be modified and other components need to be included to complete the set of constraints. They did not consider PRC for draw rate constraint.

Parkinson [15] developed three integer programming (IP) models: Basic, Malkin, and 2Cone, for finding the optimal opening sequence in an automated manner. All three models share three basic constraints. The start-once constraint ensures that each drawpoint is opened only once. The global capacity constraint ensures that the number of active drawpoints does not exceed the downstream-processing capacity. The big disadvantage of this research was the lack of draw rate constraint. Parkinson assumed a constant draw rate for the life of the mine.

Epstein et al. [16] presented and solved a MIP model with an objective function of maximizing the NPV that was successfully used in Chilean copper mines by Codelco for both underground and open-pit extraction. Their model uses drawpoint as the exploitation unit for underground operations. The drawpoint is represented as a column composed of a discrete number of blocks. In the model, the sequence is an input for a constraint in the model. Other constraints that appear are production capacity, maximum extraction rate per drawpoint, maximum allowed horizontal extraction per sector planted in terms of areas, not shapes, regularity in heights, and interaction with neighborhoods (considering interactive draw).

Alonso-Ayuso et al. [17] considered a MIP medium range planning problem for the El Teniente mine in Chile to maximize NPV by introducing the uncertainty problem. They presented a stochastic version of copper extraction planning problem under uncertainty in the (volatile) copper prices and used only some operational constraint. But they did not consider the draw control mechanism.

Khodayari and Pourrahimian [18] presented a comprehensive review of application of operations research in block-cave production scheduling. They summarized researchers' efforts of using mathematical programming for developing methodologies to optimize production schedules in block-caving operations. It was stated that more works need to be done on including geotechnical aspects of the operations, the uncertainty associated with material flow, and price uncertainties in the production scheduling. In addition, clustering methods was suggested as a solution for reducing the size of the problem in block-cave mining.

Rubio and Fuentes [4] described a simulation methodology to compute production schedule reliability and derive into the risk-return space such that mine planners can provide a portfolio of planning scenarios to decision makers. The construction of scenarios needs to be efficiently managed in order to cover the whole space of technical options feasible for a mine operation. Maximum tonnage that can be drawn from drawpoints based on the overall drawing strategy assumed as the objective function. They used a simple linear mathematical formulation for draw rate constraint. Khodayari and Pourrahimian [3] applied mixed-integer quadratic programming (MIQP) in the long-term scheduling of block-cave mines. Their aim was to minimize deviations of the production schedule from targets while operational constraints are satisfied.

Some of the methods which were presented above, did not incorporate, operational performance to adjust medium- and long-term plans because of loss of geotechnical rules in the modeling of actual draw management systems. Including the PRC constraint in the mathematical model can cause complexity and as a result a significant increase in the size of the problem.

Cluster analysis organizes data by abstracting underlying structure either as a grouping of individuals or as a hierarchy of groups. The representation can then be investigated to determine whether the data grouping is according to preconceived ideas or, if not, to suggest new experiments [19]. The hierarchical algorithm is a statistical method used to build clusters gradually based on the measured characteristics. It starts with each case in a separate cluster and then combines the cluster sequentially, reducing the number of clusters at each step, until one cluster is left. When there are N cases, the algorithm consists of N–1 clustering steps or fusions. In simple terms, a sequence of partitions of N samples into C clusters is considered. The first of these is a partition into N clusters, each containing exactly one sample. The next is a partition into N–1 clusters, and then into N–2, and so on [20].

In brief, clustering is defined as the process of grouping similar entities together so that maximum intra-cluster similarity and inter-cluster dissimilarity are achieved [20-22]. Clustering can be categorized into two major groups: hierarchical and partitional clustering.

Epstein et al. [23] used aggregation for underground block-sequencing operations and embedded it into an optimization-based heuristic. Weintraub et al. [24] considered a priori and a posteriori aggregation clustering methods based on a K-means algorithm to reduce the size of the MIP model which they had developed for El Teniente, a large Chilean block-caving mine. In establishing a method for measuring the dissimilarity between clusters, they considered a number of characteristics: tonnage, the copper grade, the molybdenum grade, and the rate of extraction. Each characteristic had a different importance, so, a set of weights associated with the characteristics was defined. Weintraub and his colleagues also identified a number of constraints that need to be satisfied: (1) each cluster can be extracted only once; (2) the defined sequence of extraction must be satisfied; (3) the allowable extraction rate and capacity of extraction must not be exceeded; and (4) flows and logical relationships between variables must be conserved. The objective function was maximizing the profit. The planning process was considered for a 25-year horizon. The authors noted that their aggregation procedure faced difficulties in defining aggregations and weights. Because each characteristic has different levels of importance, a set of weights associated with the characteristics was defined. This was done by mine planning experts. Draw rate as one of the important parameters was not established as a characteristic to measure the dissimilarity between clusters.

Newman and Kuchta [30] formulated an MIP model to schedule an iron-ore production over multiple time periods. To overcome the size of problem, they designed a heuristic approach based on solving a smaller, more tractable model. In this approach, they aggregated the time periods and then solved the original model using information gained from the aggregated model. They calculated an upper bound based on the difference between the original optimum solution and the restricted model. The non-aggregated models in Newman and Kuchta consist of 500 binary variables, while aggregated models consist of 260 binary variables [25].

Pourrahimian et al. [26, 27] applied an MILP model to develop a practical optimization framework for cave mining production scheduling. They presented a multi-step method for long-term production scheduling of block caving. To overcome the problem about the size of mathematical programming models and to generate a robust practical near-optimal schedule, they used a hierarchical clustering method. Their model aims to maximize the NPV of the mining operation at three different levels of resolution: (i) aggregated drawpoints (cluster level); (ii) drawpoint level; and (iii) drawpoint-and-slice level. Their model extracts material from drawpoints within an acceptable rate, however, it does not consider the geotechnical properties of the rock mass through the draw rate constraint.

One of the shortcomings of these methods is their dependency on the definition of similarity and their high sensitivity to the weights used in determining similarity. The proposed clustering algorithm in this paper is based on a hierarchical approach and is specifically developed to be used in solving block-cave mine production scheduling problem.

3. Clustering algorithm

Clustering is defined as the process of grouping similar objects together in a way that maximum intra-cluster similarity and inter-cluster dissimilarity are achieved. Hierarchical clustering procedures are among the best known statistical methods of clustering.

Clustering is applied in planning programs due to its low computational effort requirement and the reasonable quality of the solutions that generates [6]. After applying clustering in the MILP model, the percentage error in the value of the objective function must be negligible and the reduction of solving time must be significant when comparing the original model with the new clustered model. Determining the similarity index for grouping objects in clusters is the main key in clustering algorithms. However, the similarity of constituent items is not always the sole factor in determining the groups. One can name situations in which generated clusters have to satisfy some constraints, such as mutually exclusive and inclusive objects, minimum and maximum cluster sizes, and constraints on the cluster shapes. Although it is possible to form a mathematical model for finding the optimum clustering scheme and add different constraints to the formulations, the clustering problem has been proven to be an NP-Hard problem [4, 5].

Hierarchical clustering can be divided into two distinct classes; agglomerative and divisive. Agglomerative (bottom up, clumping) procedures start with n singleton clusters and form the sequence by successively merging clusters. Divisive (top down, splitting) procedures start with all of the samples in one cluster and form the sequence by successively splitting clusters. The computation required to go from one level to another is simpler for the agglomerative procedures than the divisive one [20]. Aggregation techniques are highly dependent on the structure of the problem, and, in general, are tailored specifically for a class of problems or even for a specific instance of a problem [25]. Clustering reduces the number of variables, especially binary variables in the MILP formulation, to make the formulation computationally tractable.

In this study, a multi-step approach is developed to generate aggregates with respect to the direction of mining and control the shape and size of the generated aggregates. The methodology can determine the best order of extraction of material from the clusters by maximizing the net present value (NPV) of the operation over the life of mine. In the clustering method it has been assumed that the scheduled portion to be extracted from each cluster is taken from all of the drawpoints, based on the ratio of each drawpoint's tonnage in the cluster. The maximum draw rate ($MaxDR_i$) of drawpoint *i* is calculated from the PRC by considering depletion percentage (M). Equation (1) represents the maximum draw rate of drawpoint response to the PRC:

$$MaxDR_i = \left(M - \frac{MinDR_i}{Ton_i}\right) \times Ton_i \tag{1}$$

Where $MinDR_i$ is the minimum draw rate of drawpoint i which is a given value for mines according to the geotechnical properties of rock mass and Ton_i is the overall tonnage of draw column associated with drawpoint i.

Bartlet [28] recommends starting the caving where the weak rock is located so that the hydraulic ratio can be reached earlier in the life of the mine and the time required to recover the investment is shortened.

Another method, which consists of starting where the high-grade ore is located, leads to early payback of the investment or higher NPV [29]. The direction of undercut developing into the principal stress direction will influence the magnitude of abutment stresses. Therefore, to reduce clamping stresses in the cave back, the undercuts are usually extracted in the direction of the maximum principal stress [30].

Considering the direction of advancement in forming the clusters is a key strategy when dealing with economical or geotechnical problems. It is essential to develop a direction factor to be included in the similarity index and account for the advancement direction. For this purpose, the method by Tabesh and Askari-Nasab was modified for its application in block-cave mining [31]. According to the Tabesh and Askari-Nasab method, after determining the advancement direction, the planner should define two points at the starting and ending point in the direction of advancement. Afterward, the direction factor can be calculated using equation (2).

$$N_i = sign\left((N_i^1)^2 - (N_i^2)^2\right) \times \sqrt{\left|(N_i^1)^2 - (N_i^2)^2\right|} \tag{2}$$

Where N_i^1 and N_i^2 are the distance from drawpoint i to start and end points respectively. The sign function returns +1 if the value is positive and -1 if the value is negative.

3.1. Multi-similarity index

Aggregation procedure needs a similarity measure or similarity index that quantifies the similarity between two objects. Various properties can be taken into account when defining similarities between draw columns. In this section, a multi-similarity index clustering algorithm is developed for draw column aggregation. The multi-similarity indices are used to remove the similarity index dependency for the weight factors that are defined by the planner in the existing models.

Increasing the number of properties engaged in similarity calculations increases the complexity of the index, in terms of not representing a unique physical attribute. Multi-similarity indexes aggregate the draw columns into clusters based on center-by-center distance, grade distribution, maximum draw rate according to the PRC, and advancement direction. The general procedure of proposed algorithm is as follows:

1. Define the number of required similarity indexes according to the mining operation.
2. Define a search radius.
3. Each draw column is considered as a cluster. The similarities between clusters are the same as the similarities between the objects they contain in each index.
4. Define the maximum number of required clusters and the maximum number of allowed draw columns within each cluster for each index.
5. Similarity values are calculated for the considered similarity index.
6. The most similar pair of clusters is merged into a single cluster.
7. The similarity between the new clusters and the rest of the clusters is calculated. Steps 3 to 6 are repeated until the maximum number of clusters is reached or there is no pair of clusters to merge because the maximum number of allowed draw columns has been reached.
8. For the next similarity index, define an intra-cluster adjacency matrix for draw columns that are located within two different clusters.
9. Repeat steps 3 to 7 for the similarity index defined in step 8.

For the first step, the similarity index is calculated based on the distance and the most similar pair of clusters is merged into a single cluster (equation (3)):

$$SI_1 = \frac{1}{D_{ij} \times N_{ij\text{-}SI_1}} \times A_{ij} \tag{3}$$

Where SI_1 is the similarity index of step 1 (distance), $\frac{1}{D_{ij} \times N_{ij\text{-}SI_1}}$ is the similarity value between draw columns i and j, D_{ij} is the normalized distance value between the center line of draw columns i and j, $N_{ij\text{-}SI_1}$ is the normalized Euclidean distance between values N_i and N_j for SI_1, and A_{ij} is the adjacency factor between draw columns i and j. If the distance is less than the defined search radius, A_{ij} is 1; otherwise, it is 0. The similarity between the new clusters and the rest of clusters is calculated. After calculating the similarity, the mentioned steps are repeated until the maximum number of clusters is reached or there is no pair of clusters to be merged, because the maximum number of allowed draw columns has been reached.

For the second step, similarity based on the maximum allowable draw rate, an intra-cluster adjacency matrix for draw columns that are located within two different clusters is required (equation (4)):

$$SI_2 = SI_1 \times \frac{1}{MaxDR_{ij} \times N_{ij\text{-}SI_2}} \times ISA_{ij} \tag{4}$$

Where $SI_1 \times \frac{1}{MaxDR_{ij} \times N_{ij-SI_2}}$ is the similarity value between draw columns i and j, and ISA_{ij} is the second-inter-cluster adjacency factor between draw columns i and j. If draw columns i and j are in the same cluster as they were in the first step, ISA_{ij} is 1; otherwise, it is 0.

In the third step, similarity is calculated based on the grade of draw columns (equation (5)):

$$SI_3 = SI_1 \times \frac{1}{Grade_{ij} \times N_{ij\text{-}SI_3}} \times ITA_{ij} \tag{5}$$

Where $SI_1 \times \frac{1}{Grade_{ij} \times N_{ij-SI_3}}$ is the similarity value between draw columns i and j, $Grade_{ij}$ is the normalized grade difference between draw columns i and j, and ITA_{ij} is the third-intra-cluster adjacency factor between draw columns i and j. If draw columns i and j are in the same cluster as they were in the second step, ITA_{ij} is 1; otherwise, it is 0. This algorithm controls practical cave advancement.

4. MILP model

Developing any model requires some decision variables, sets, indices, and parameters that correspond to a scheduling program. Indices are for drawpoints and periods. The model identifies two types of variables: (i) continuous and (ii) binary. $U_{cl,t} \in [0,1]$ is the portion of cluster cl to be extracted in period t. The binary variable indicates the time when the cluster is opened, active, or in any working states during a specified time period. $A_{cl,t} \in \{0,1\}$ *is* equal to 1 if cluster cl is active in period t; otherwise it is 0. $Z_{cl,t} \in \{0,1\}$ *is* controlling the precedence of extraction of clusters. It is equal to 1 if extraction from cluster cl is started in period t; otherwise, it is 0. $cl \in \{0,CL\}$ is an index for clusters, $t \in \{0,T\}$ is an index for scheduling periods, and l is an index for a cluster belonging to set S_{cl}. For each cluster, cl, there is a set S_{cl} defining the predecessor clusters that must be started prior to extraction of cluster cl.

Mixed-integer linear programming (MILP) formulation presented in this paper maximizes the NPV subject to various operational and geotechnical constraints. The model is developed in MATLAB [32] and solved using IBM/CPLEX [33]. The mathematical equations are presented as follows:

$$Maximize \sum_{cl=1}^{CL} \sum_{t=1}^{T} \left[\frac{\mathrm{Re}_{cl}}{(1+i)^t} \right] \times U_{cl,t} \tag{6}$$

$$M_l \leq \sum_{cl=1}^{CL}(Ton_{cl}) \times U_{cl,t} \leq M_u \tag{7}$$

$$\sum_{cl=1}^{CL}(Ton_{cl} \times (G_{l,cl,t} - \widetilde{G}_{cl,t}) \times U_{cl,t} \leq 0 \tag{8}$$

$$\sum_{cl=1}^{CL}(Ton_{cl} \times (\widetilde{G}_{cl,t} - G_{u,cl,t}) \times U_{cl,t} \leq 0 \tag{9}$$

$$A_{cl,t} \leq L.U_{cl,t} \tag{10}$$

$$U_{cl,t} \leq A_{cl,t} \tag{11}$$

$$\sum_{cl=1}^{CL} A_{cl,t} \leq N_{Acl,t} \tag{12}$$

$$Z_{\mathrm{cl},t} - \sum_{j=1}^{t} Z_{l,j} \leq 0 \tag{13}$$

$$\sum_{t=1}^{T} Z_{\mathrm{cl},t} = 1 \tag{14}$$

$$A_{\mathrm{cl},t} - A_{\mathrm{cl},(t-1)} \leq Z_{\mathrm{cl},t} \tag{15}$$

$$A_{\mathrm{cl},1} = Z_{\mathrm{cl},1} \tag{16}$$

$$N_{Nl,\mathrm{cl},t} \leq \sum_{\mathrm{cl}=1}^{CL} Z_{\mathrm{cl},t} \leq N_{Nu,\mathrm{cl},t} \tag{17}$$

$$\sum_{\mathrm{cl}=1}^{CL} Z_{\mathrm{cl},1} \leq N_{A\,\mathrm{cl},1} \tag{18}$$

$$\sum_{t=1}^{T} U_{\mathrm{cl},t} \leq 1 \tag{19}$$

$$\sum_{t=1}^{T} A_{\mathrm{cl},t} \leq Max_{Life-Activity} \tag{20}$$

$$U_{\mathrm{cl},(t+m)} \times Ton_{\mathrm{cl}} - \left(\frac{(DR_{Ramp,\mathrm{up},T} - DR_{l,\mathrm{cl},t})}{1 - \frac{DR_{l,\mathrm{cl},t}}{Ton_{\mathrm{cl}}}} \right) \times \sum_{t=1}^{t+m} U_{\mathrm{cl},(t+m)} \leq DR_{l,\mathrm{cl},t} - \left(\frac{(DR_{Ramp,\mathrm{up},T} - DR_{l,\mathrm{cl},t})}{1 - \frac{DR_{l,\mathrm{cl},t}}{Ton_{\mathrm{cl}}}} \right) \times \frac{DR_{l,\mathrm{cl},t}}{Ton_{\mathrm{cl}}} \tag{21}$$

$$U_{Steady,T} \times Ton_{\mathrm{cl}} \leq DR_{u,\mathrm{cl},t} \tag{22}$$

$$U_{\mathrm{cl},(t+m)} \times Ton_{\mathrm{cl}} + \left(\frac{(DR_{Ramp,down,T} - DR_{l,\mathrm{cl},t})}{1 - \frac{DR_{l,\mathrm{cl},t}}{Ton_{\mathrm{cl}}}} \right) \times \sum_{t=1}^{t+m} U_{\mathrm{cl},(t+m)} \le DR_{Ramp,down,T} + \left(\frac{(DR_{Ramp,down,T} - DR_{l,\mathrm{cl},t})}{1 - \frac{DR_{l,\mathrm{cl},t}}{Ton_{\mathrm{cl}}}} \right) \times \frac{DR_{l,\mathrm{cl},t}}{Ton_{\mathrm{cl}}} \tag{23}$$

$$DR_{l,\mathrm{cl},t} \times Z_{\mathrm{cl},t} - Ton_{\mathrm{cl}} \times U_{\mathrm{cl},t} \le 0 \tag{24}$$

The objective function, equation (6), is composed of the economic value of the cluster, the continuous decision variable, and the discount rate.

Knowledge, experiments of mine planners, and corresponding planning horizons have a critical role in the process of assigning constraints to the optimization problems. These constraints appear in several different forms: geotechnical, grades, period, advancement direction, and priority of the clusters, productivity, production rates, and many others that depend on the mining method.

Equation (7) ensures that the total tonnage of material extracted from active clusters in each period is within an acceptable range that allows flexibility for potential operational variations. Where Ton_{cl} is the total tonnage of material within the cluster *cl*, M_u and M_l are the upper and lower limits of mining capacity in period *t*, respectively.

Equations (8) and (9) force the mining system to achieve the desired production grade. The average grade of the element of interest has to be within the acceptable range. Where $\overline{G}_{cl,t}$ is the average grade of the cluster *cl*, and $G_{u,cl,t}$ and $G_{l,cl,t}$ represent the upper and lower limits of the acceptable average head grade of cluster *cl* in period *t*.

According to Equations (10), (11) , and (12) the number of active clusters must not exceed the allowable number in each period and has to be constrained according to the size of the ore-body and the available infrastructure and equipment. Where $N_{Acl,t}$ is the maximum allowable number of active clusters in period *t*. The precedence between clusters is controlled in a horizontal direction. Controlling the order of extraction of clusters in an advancement direction is the goal of the precedence constraint. According to the advancement direction, for each cluster *cl* there is a set S^{cl} which defines the predecessor clusters among adjacent clusters that must be started before cluster *cl* is extracted. Equation (13) controls the precedence of extraction. In equation (13), *l* is the index for a cluster belonging to set S^{cl}, $Z_{l,t}$ ensures that all clusters belonging to set S^{cl} are started before or in period *t*, if cluster *cl* is started in period *t*.

Equations (14) and (15) force the mining system to extract material from each cluster continuously after opening until closing. Equation (16) is only used for period 1. Equations (17) and (18) control the number of new clusters to be opened at any given time within the scheduled horizon. This parameter is determined based on the footprint geometry, the geotechnical behavior of the rock mass, and the existing infrastructure of the mine. $N_{Nl,cl,t}$ and $N_{Nu,cl,t}$ are the lower and upper limits for the number of new clusters, the extraction from which can start in period *t*. The number of new clusters that should be opened in period 1 is equal to the number of active clusters. Equation (19) ensures that the model cannot extract more than the available material in each cluster.

Maximum activity life, controls the number of periods in which the cluster is active. This constraint ensures that the extraction rate from the cluster is large enough to maximize the NPV and small enough to prevent over-dilution. Equation (20) indirectly affects the draw rate by controlling the number of activity periods of any cluster. Greater activity life results in higher recompaction and dilution. $Max_{Life-Activity}$ is the maximum number of allowable periods in which any cluster can be active.

Draw control in a caving operation means optimizing the extraction from drawpoints in order to achieve the production goals while minimizing the dilution. In addition, the draw rate controls the distribution of the induced stresses in the caving environment [34].

Production rates are specified as tonnes per square meter per day per drawpoint. The changes in draw rate are normally classified as a drawpoint opening to ramp up production, steady state production, and ramp down to closure. Such pattern named as ramp up-steady-ramp down (USD) (see Fig 1). The USD model is best because the low draw rate in the early years of the life of drawpoints is caused by the geotechnical characteristics of the surrounding environment aligned with the caved material, and in fact, increasing stress caused by draw and caving process relaxes with a relatively soft tendency. Therefore, appropriate management of stress relaxation can be done. The main goal of draw rate formulation is to find the draw rate of each drawpoint in each period during the optimization of scheduling based on the defined objective function, constraint, and PRC.

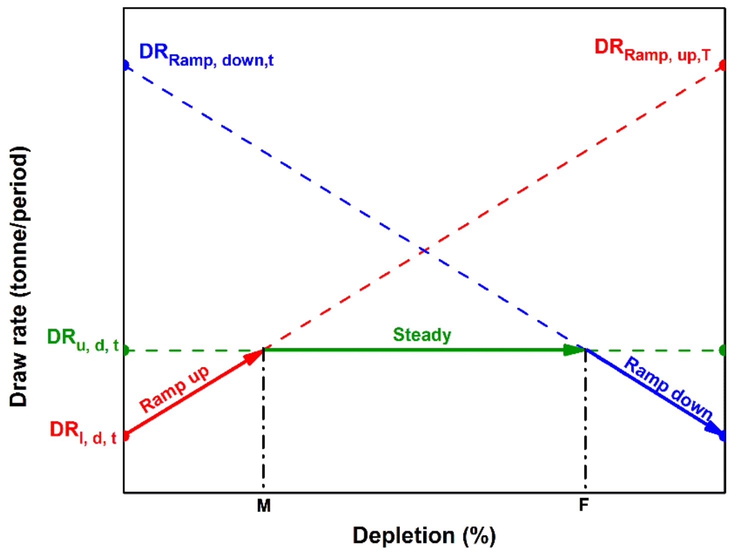


Fig 1. PRC for the draw rate control system

It should be noted that the PRC of each cluster is determined based on the number of drawpoints and the PRC of the drawpoints within the cluster. The problem can be formulated for the given PRC Based on the equations (21), (22) and (23). $DR_{u,cl,t}$ and $DR_{l,cl,t}$ are the maximum and minimum possible draw rate of cluster *cl* in period *t*, *M* is the maximum allowable depletion to reach $DR_{u,cl,t}$, *F* is maximum allowable depletion to reach ramp-dawn region after steady production, U_t is the percentage of depletion at the first period extraction of the cluster Draw control in a caving operations means optimizing the extraction from drawpoints in order to achieve the production goals while minimizing the dilution. In addition, the draw rate controls the distribution of the induced stresses in the caving environment [34]. $U_{d,(t+m)}$ is the percentage of total depletion after *m* period of extraction, $DR_{Ramp.up,t}$ is the draw rate with full depletion for ramp up states, and $DR_{Ramp,down,t}$ is the draw rate with full depletion for ramp down states. Equation (21) shows the mathematical structure for the area under the ramp up region. Also, equations (22) and (23) are related to the steady and ramp down regions respectively.

5. Illustrative Example

The production schedule of 2,487 draw points according to defined PRC and cluster approach is investigated in this section. The total tonnage of material is 803.91 (Mt) with an average density of 2.2 (t/m^3) and an average grade of 0.36%Cu. Fig 2 illustrates the tonnage and grade distribution of the draw columns. The performance of the proposed MILP models was analyzed based on maximizing the NPV at a discount rate of 12%. The model was tested using a Dell Precision T7600 computer with Intel(R) Xeon(R) at 2.3 GHz, with 64 GB of RAM. The maximum depletion of the drawpoints from the ramp up to steady (M) and steady to the ramp down (F) were 40% and 85%, respectively. The draw control system, by enrolling an exact production rate curve seeks to optimize and present a practical block-cave production schedule. A gap tolerance (EPGAP) of 5% was used as an optimization termination criterion. The other scheduling parameters have been summarized in **Error! Reference source not found.**.

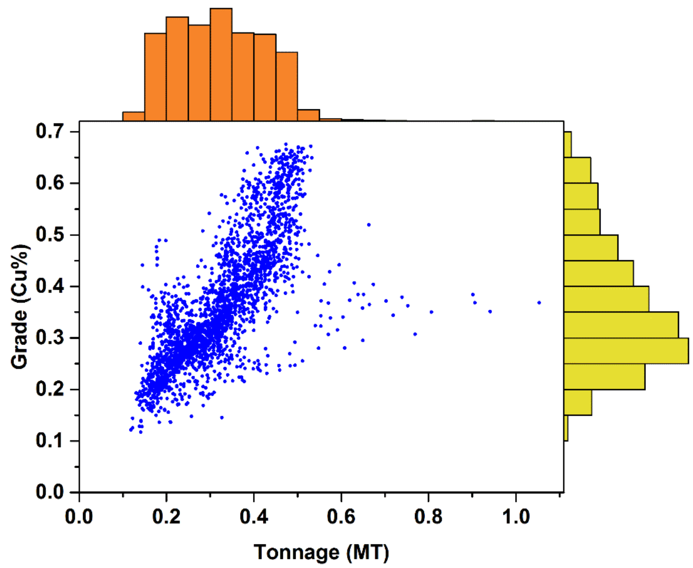
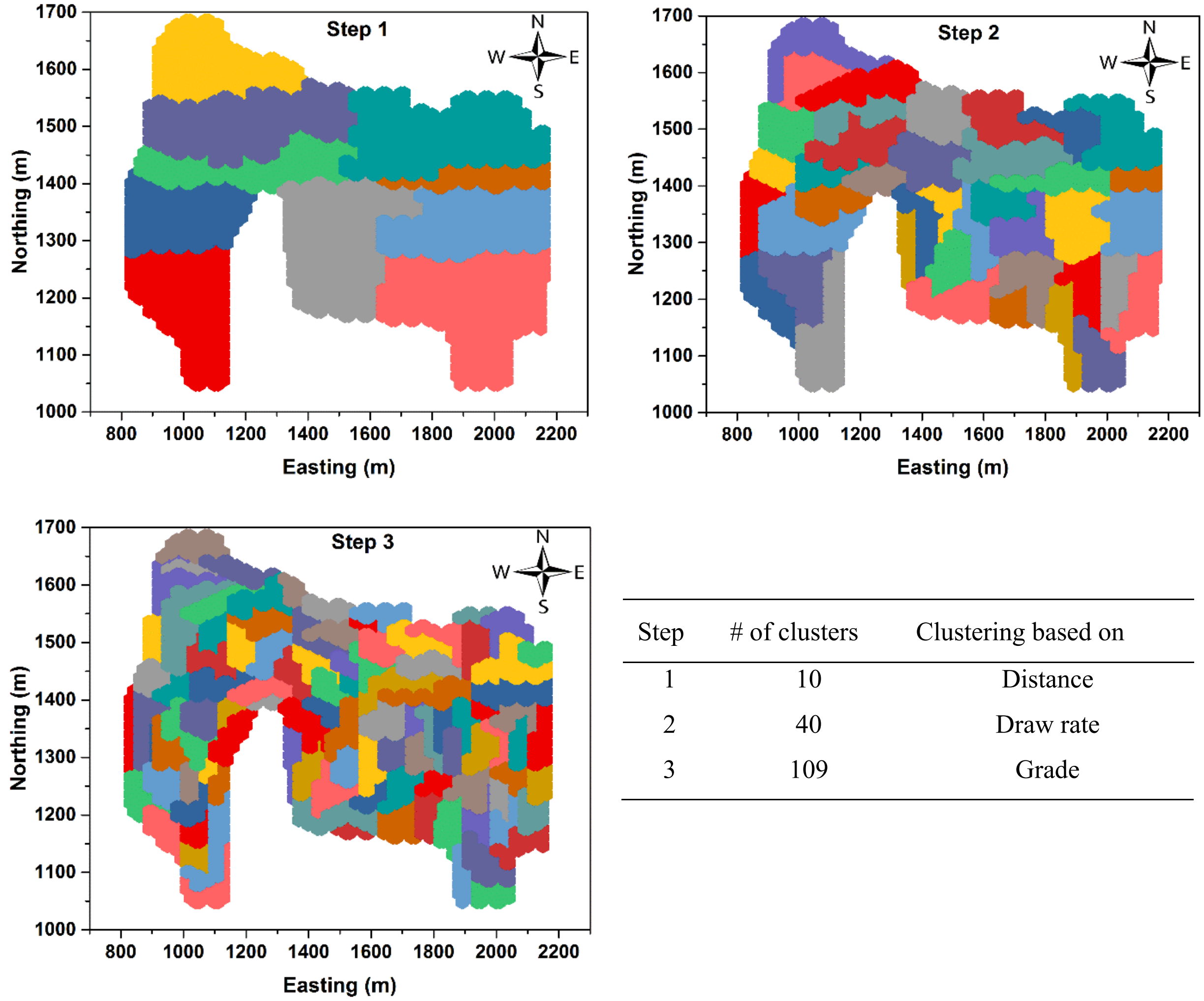


Fig 2. Tonnage and grade distributions of draw columns

Table 1. Production scheduling parameters

Parameters		Value
Maximum activity (periods)		5
Mining capacity (Mt)		15 – 27.5
Draw rate of draw columns (kt/period)		30 – 100
No. of new clusters per period		0 – 11
Production grade (%Cu)		0.3 – 0.6
No. of maximum active clusters per period		25
Max. number of clusters	First step	10
	Second step	40
	Third step	109
Max. number of draw columns	First step	350
	Second step	80
	Third step	25
Adjacency radius (m)		22

Fig 3 shows the proposed clustering method for 2,487 drawpoints. The clustering was done in three steps. These steps are based on (i) the distance between drawpoints in the advancement direction, (ii) draw rate of drawpoints, and (iii) grade of draw columns. The advancement direction was determined based on the method presented by Khodayari and Pourrahimian [35]. The advancement direction is from south to north. The maximum number of clusters which was defined in the first, second, and third step were 10, 40, and 109 respectively.



Step	# of clusters	Clustering based on
1	10	Distance
2	40	Draw rate
3	109	Grade

Fig 3. Application of the multi-index clustering method for 2,478 draw columns

The problem was modeled both with and without clustering approach. The total number of constraints in the model without clustering was 610,548. The numbers of continuous and binary variables were 79,296 and 158,592 respectively. This model did not reach a solution after being ran for 15 days. On the other hand, the model with the clusters was built on 30,516 constraints, and the number of continuous and binary variables was 3,488 and 6,976 respectively. Using the multi-similarity index aggregation system resulted in 95% reduction in the number of binary variables. The cluster model was solved in 37(hr):48(min):11(sec). 761.87Mt ore was extracted during 32 years of production with the NPV of $304.6 B.

Fig 4 shows the cash flow, the production tonnage, and average grade of production in each period for the cluster model. The ramp up and down for the total production is achieved in the resulted production plan.

Fig 5 shows the grade distribution of the clusters. Fig 6 illustrates the starting period of the clusters in the cluster model during the life of the mine. The start period of drawpoints shows the advancement direction of caving has been achieved within in the optimization. To follow the defined sequence of extraction, the high-grade clusters are extracted during periods 15 to 21 (Fig 6). As a result, the grade of production increases during that period of time (Fig 4). Because of the application of the production rate curve for draw control, it is expected to have less dilution during the life of mine.

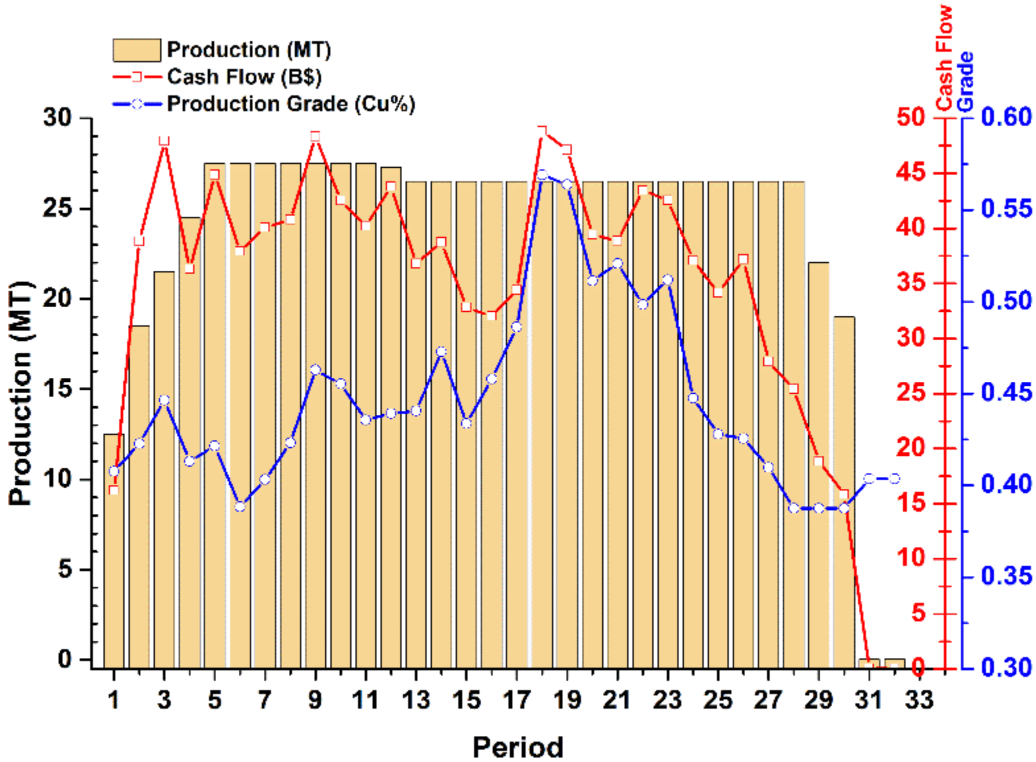


Fig 4. Cash flow, yearly production and average grade of production in the cluster model

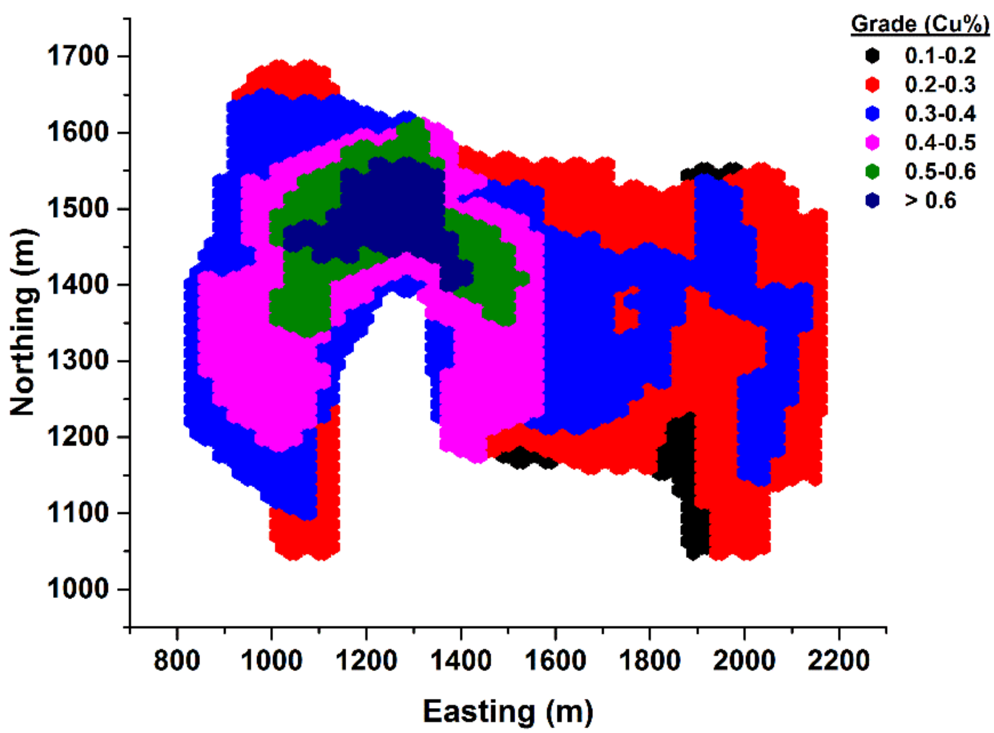


Fig 5. Grade distribution in the cluster model

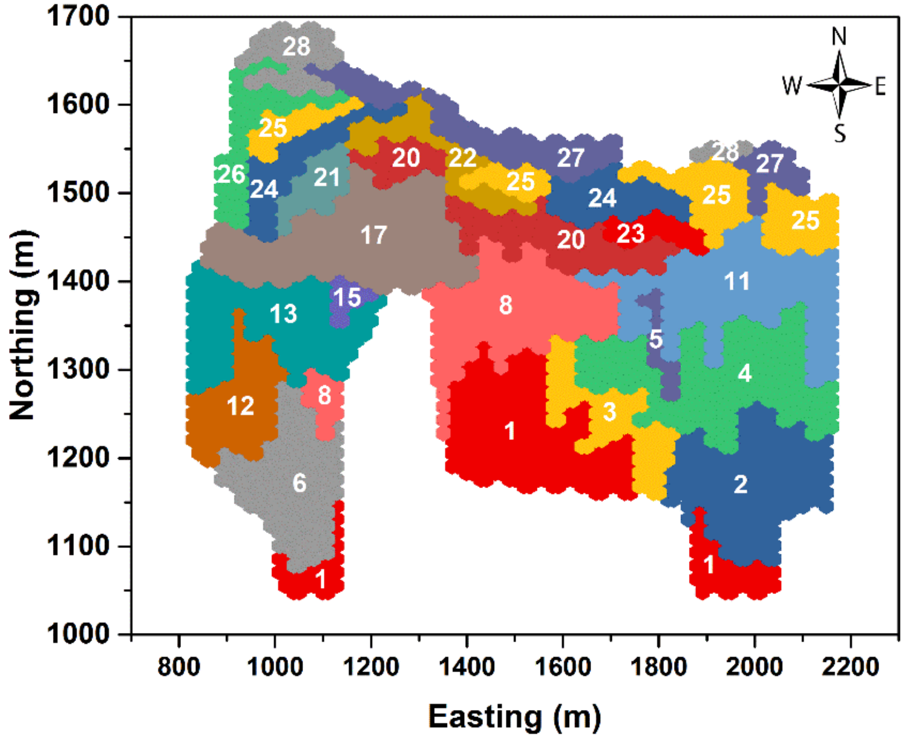


Fig 6. Starting period of the different areas in the mine over the life of mine

Fig 7 shows the maximum number of active clusters and number of new clusters which had to be opened in each period. The number of active clusters in period one is equal to the number of new clusters which opened. From periods 12 to 15, this number gradually reduces. The number of new clusters opened in period one could be equal to the maximum allowable number of active clusters to reach the required production in this period. There was no need to open new clusters in periods 7, 9, 10, 14, 16, 18, 19, 20, 30, 31, and 32.

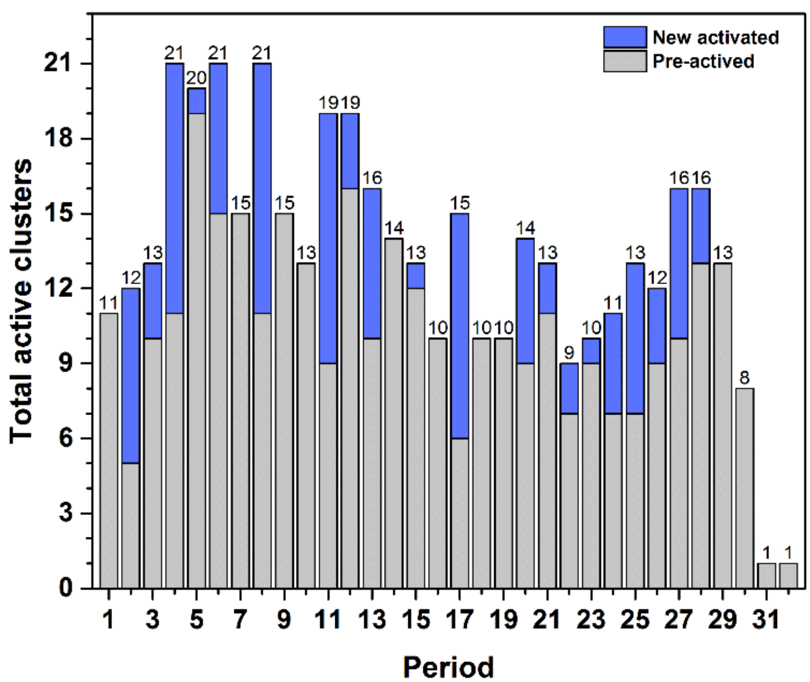


Fig 7. Number of active and new clusters in the model

Fig 8 presents the draw rate changes for three different clusters in the cluster model. According to the defined PRC, clusters cannot be depleted arbitrarily. On the other hand, the material with a lower economic value and grade can remain in the clusters because of the defined objective function and the constraints. The minimum and maximum draw rate of each drawpoint are 30,000 (kt/period) and 100,000 (kt/period), respectively. The draw rate of each cluster varies based on the number of draw columns in the cluster. In Fig 8, it can be seen that extraction from cluster 29 is started in period 25 with the minimum acceptable draw rate, then it gradually increases to reach the maximum acceptable draw rate in period 27, the steady state with the maximum draw rate continues for two periods, and finally the draw rate reduces till it is closed. Cluster 29 contains 30 drawpoints, so the minimum and maximum draw rates for this cluster are 900 and 3000 (kt/period), respectively.

The results show that all the defined constraints have been satisfied. The draw rates for each cluster and starting and finishing periods are the outputs of the optimization. The model extracts the material from each cluster based on the defined draw rate model while maximizing the NPV of the operation.

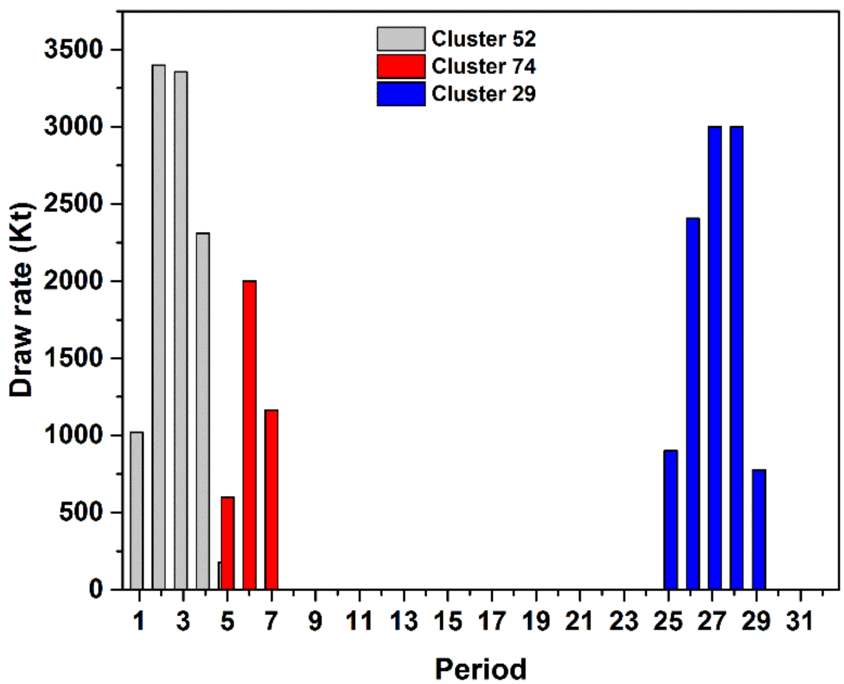


Fig 8. Draw rate of clusters 29, 52, and 74

6. Conclusion

This paper presented a multi-similarity index aggregation approach for the oversize MILP models. The proposed model maximizes the NPV subject to operational and geotechnical constraints. The MILP formulation for a block-cave production schedule was developed, implemented, and tested in IBM/CPLEX environment. A practical draw control system was considered in the optimization model based on PRC in order to manage draw rates of block-cave operations. Because of the size of the problem, the model without clustering could not solved in a reasonable time, therefore, the cluster model was implemented. The clustering techniques resulted in 95% of the reduction in the number of binary variables which made it possible to solve the same problem in an acceptable processing time. This solution time would enable the mine planner to analyze different scenarios during the feasibility studies. The presented aggregation approach eliminates dependency to the weight factor in clustering technique, as a result, human errors will not affect the optimality of the production schedule. Using the presented clustering approach and the MILP formulation, production schedule of large-scale block cave operations can be optimized during the life of mine.

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Determination of Optimum Drawpoint Layout in Block Caving using Sequential Gaussian Simulation

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ABSTRACT

The economics of today's mining industry are such that the major mining companies are increasing the use of massive mining methods. Caving methods have become the underground bulk mining method of choice and are expected to continue as such in the foreseeable future. Caving methods are favoured because of their low cost and high production rates. They offer a much smaller environmental footprint compared to equivalent open pit operations due to the much smaller volume of waste to be moved and handled.

Drawpoint spacing is an essential part of the block cave layout design which must be investigated carefully at the start of the project. In this paper, an overall methodology based on sequential Gaussian simulation (SGS) to obtain the drawpoint spacing is suggested. The optimized drawpoint spacing is used to maximize the profit since the extraction layout is highly essential for the economics of block caving. This study is opening a new horizon for using 'all realizations all the time' as a new approach to solve one of the trickiest elements of blocks caving.

1. Introduction

Mining companies around the world are constantly searching for tools to maximize the profitability of their projects. Optimization of design, planning, and operation are common, not only in open pit operations but also in underground mines. Among underground mining methods, block caving is typically a large-scale method and one of the few economical techniques for the extraction of deep and large low-grade material (Castro et al. 2012); however, caving is very challenging because its operational complexity is largely affected by the initial design which has limited flexibility once the drawpoints have been set. Drawpoint location is a critical element in the design of block caving layouts since spacing has a tremendous impact on production, dilution and extraction rate. The design of the production layout relies on available exploration data, geological interpretation and a geostatistical model of mine grades and geomechanical parameters.

The majority of block caving mines use kriging as the main technique to estimate resources. Therefore, the block model generated in kriging is used to generate the layout for production. There are a number of drawbacks, including:

- Only a single response can be calculated (i.e. a single NPV).
- It is difficult to assess uncertainty in the response (i.e. NPV, tonnes per year, dilution, production rate, etc.).

This paper, in its entirety, has been submitted for publication in the 1st International conference in Underground Mining Technology (UMT2017).

- The impact of the smoothing effect of kriging is difficult to quantify.

Optimization of the production layout based on kriging will not consider grade uncertainty and is, therefore, suboptimal.

An improved technique is to optimize the initial layout based on multiple models of grade that span the uncertainty in the deposit; in this work, these models (aka realizations, aka simulations) are generated with sequential Gaussian simulation (SGS). The difficulty with using multiple models is that the layout must be optimized over all n realizations; this is different than a common implementation where the layout is optimized for a kriged model (or averaged SGS realizations) and then n realizations are used to assess uncertainty in NPV, grade, etc. Rather, the optimal layout that gives the maximum NPV over all realizations is found in the proposed methodology. This allows the practitioner to select the layout that is optimal given geological uncertainty rather than select a suboptimal layout based on kriging and then assess uncertainty in a post-processing framework. This results in a better risk assessment for economic indicators as well as safety concerns.

2. Methodology

In modern geostatistics, Monte Carlo simulation (MCS) is a well-known computational algorithm; it relies on sampling conditional distributions. This algorithm is represented by the formulation of a problem with input variables (such as drillhole data, a kriged model or SGS realizations), a transfer function (such as a mine plan and resulting production per year), and the computed response variables (such as NPV) which are assessed by a probability distribution (Deutsch 2015), as shown in Fig 1.

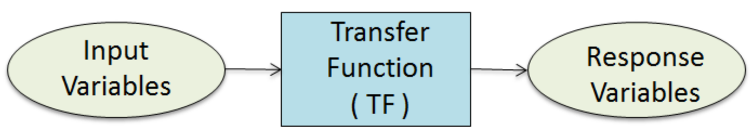


Fig. 1. Monte Carlo simulation concepts (Deutsch 2015)

First, the input variable (Cu) is simulated with SGS to generate 40 equally probable realizations. For this purpose, GSLIB, Geostatistical Software Library (Deutsch & Journel 1998), were used. Various drawpoint layouts can be selected for the transfer function and the NPV for each realization is calculated. Geovia PCBC (Personal Computer Block Caving) is used here as the transfer function and calculates NPV (USD) for a given realization; in addition to the realizations, mining parameters such as cost, fragment size, layout type, etc. are required. The transfer function converts the simulated Cu values of every realization into a response variable; in other words, one realization is considered as one block model and results in one NPV value. For a given mine layout, the final result is a distribution of 40 NPV values that quantify how optimal this layout is. The optimal layout is obtained by repeating this for different mine layouts and selecting the mine layout with the best distribution of NPV values. The most common criterion to determine the best distribution of NPV values is to select the one with the highest average NPV; it should be noted that this is not the same as optimizing the mine layout on the average model of the 40 realizations, rather, the proposed method obtains the best layout over all realizations.

The main contribution of this work is to illustrate a methodology to obtain the optimal drawpoint spacing based on a set of stochastic realizations. Moreover, advantages of the proposed approach over previous techniques are highlighted.

The present study is organized into four main steps:

- Step 1: Data analysis, statistics, and variography.
- Step 2: Geostatistical modelling with SGS.
- Step 3: Setting of mining parameters and the transfer function to calculate NPV with PCBC.

- Step 4: Output results are processed to obtain the optimized drawpoint spacing.
  - Optimal drawpoint spacing within the initial footprint.
  - Confirm the best level of extraction based on the optimal drawpoint spacing.
  - Conduct a second optimization for further refinement.

This methodology is demonstrated in a brief study that provides a concise illustration of the optimization of the drawpoint layout.

2.1. Data analysis, statistics, and variography

The study data is composed of 55 synthetic drillholes that were resampled from a confidential block model of a real block caving mine; the data used is not the original (confidential) data, rather, the geostatistical model generated from the real data is resampled to obtain this semi-synthetic realistic data. This data considers Cu as the continuous variable of interest and the ore body extents in each drillhole are known. The drilling assays have been composited to 10 m. The location of the 50 drillholes and their composites are shown in Fig 2.

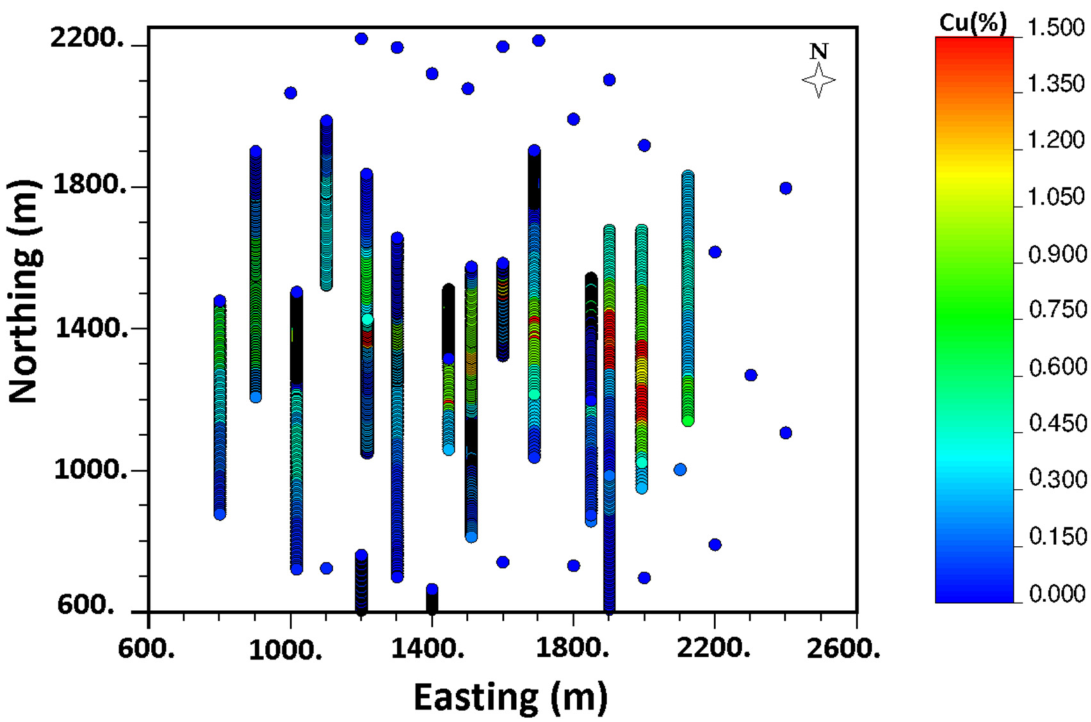


Fig 2. Composites of the drillholes used in this study

An exploratory data analysis of the composites is performed to obtain the global mean and variance of the copper grades. The global declustered mean of Cu is 0.229% with a variance of 0.122. Additional statistical analysis and geostatistical interpretations are performed to group populations before domain definition.

The geological definition was generated with implicit modelling software based on distance functions (Silva & Deutsch 2012). There are two modelling domains, Dom 1 represents the porphyry intrusion and Dom 2 is the country rock (Fig 3). The Cu distribution within the ore body is shown in Figure 5. The data are transformed to normal score values for input to SGS (Fig 4).

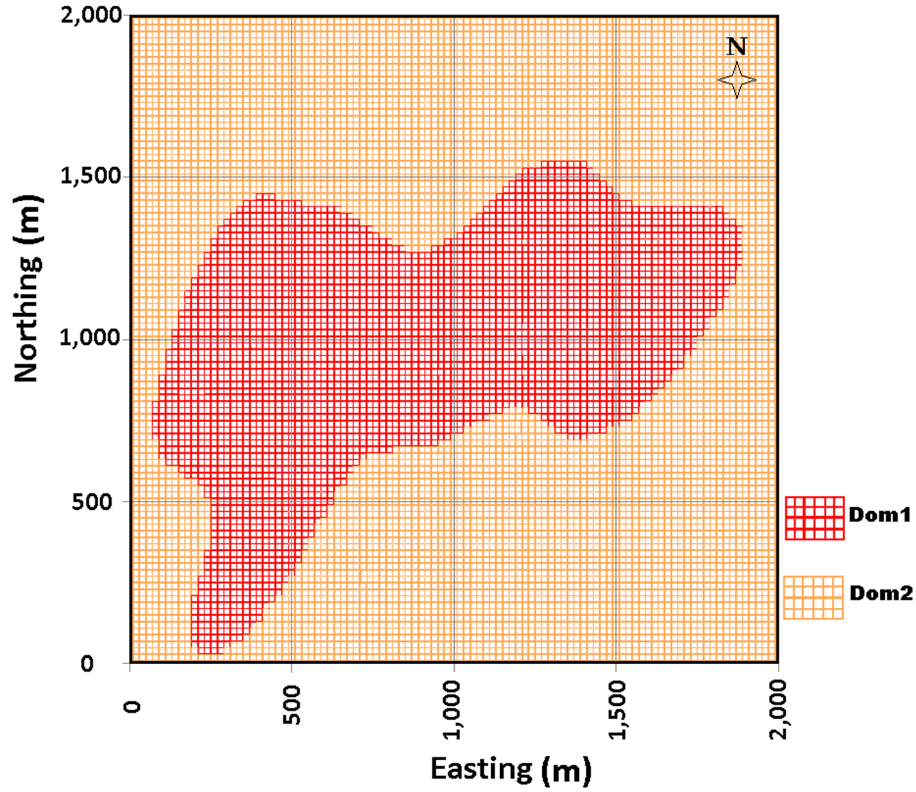
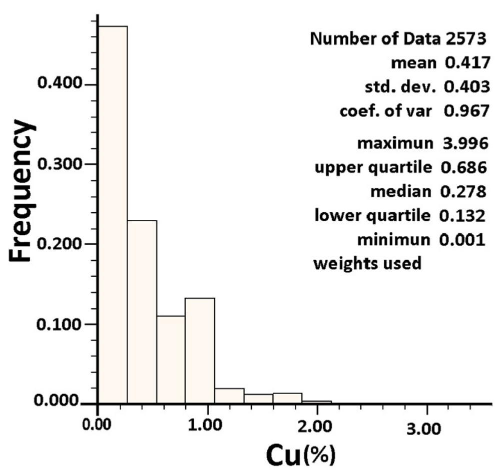
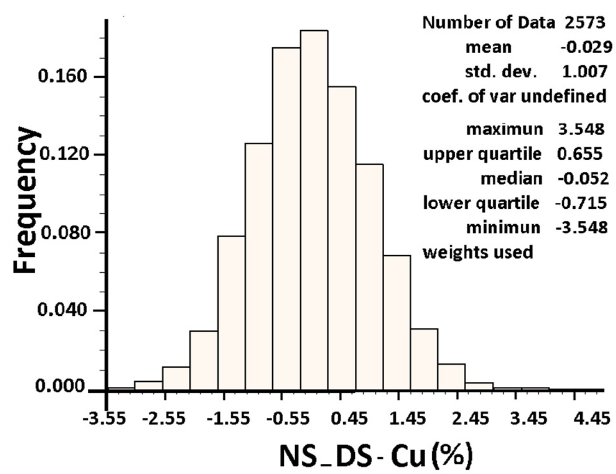


Fig 3. One slice of Dom 1 and Dom 2



(a)



(b)

Fig 4. Declustered Cu histograms for domain Dom 1. (a) original data; and, (b) normal score data

Variograms are used to quantify the spatial continuity/variability of grades. This work considers the building and modelling of two types of variograms. These are the indicator variogram model of rock type and the continuous variogram model of Cu. The horizontal experimental and modelled variogram of Cu are shown in Fig 5. These models contain two nested spherical structures, and the major (dir1) and minor (dir2) directions are 90 and 0° respectively.

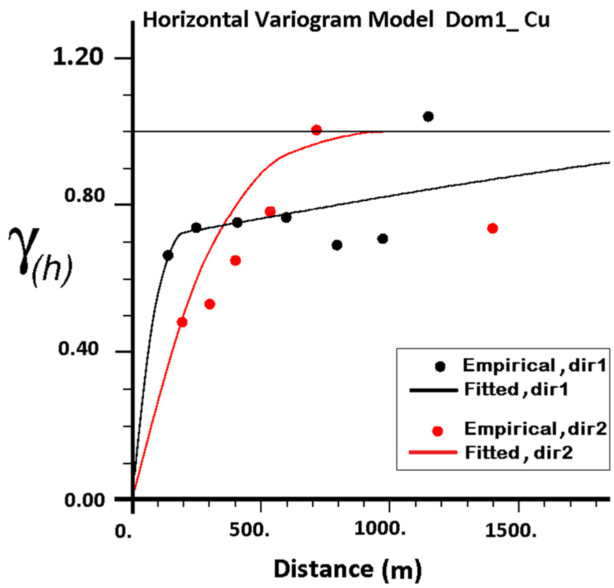


Fig 5. Fitted horizontal Cu variogram for Dom 1, the major direction (dir1) and minor direction (dir2)

2.2. Geostatistical modeling

First, 40 sequential indicator simulation (SIS) realizations are generated. The SIS realizations are used to indicate ore and waste. Modelling details include:

- The model contains 1,210,000 blocks with cell dimensions of 20 × 20 × 15 m.
- Data used for input are the declustered and normalised data (Fig 4).

To generate multiple conditional Cu realizations with SGS and SIS the modelled variograms (Fig 5) are required. Fig 6 illustrates one slice of the SGS model. Fig 7 shows good reproduction of the Cu distributions in the SGS models.

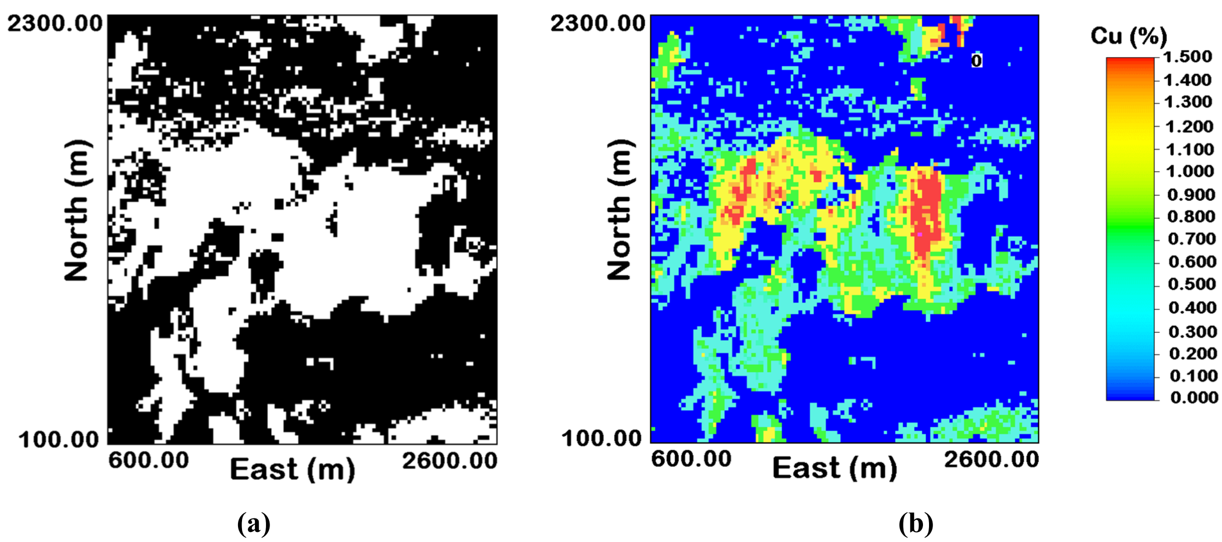


Fig 6. Slice 74, level 1150 of one SGS realization. (a) SIS realization, white = Dom 1, black = Dom 2; (b) SGS realizations of Cu

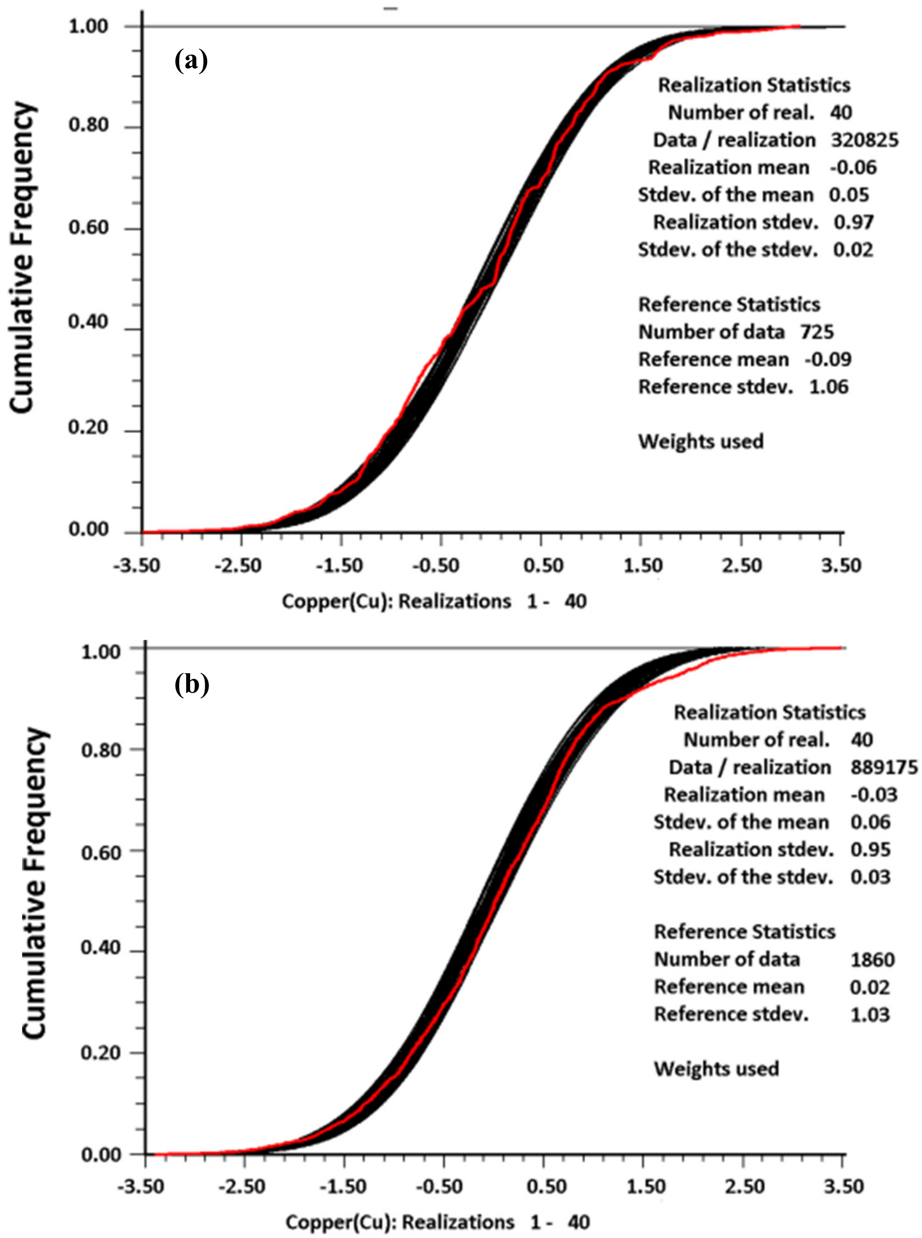


Fig 7. Cu histogram reproduction in Dom 1 (a); and, Dom 2 (b); normal score units

Setting realistic PCBC parameters is critical; however, the data for this study is confidential so values based on referenced works and realistic assumptions are used. These settings are obtained from previous engineering, economical and geotechnical studies related to block caving projects (Table 1).

First, the extraction layouts are considered. The herringbone layout (Fig 8) is used throughout the study. In the last 30 years, the most commonly used layouts are the herringbone and the El Teniente (Leach et al. 2000; Botha et al. 2008). An advantage of the herringbone layout is the load–haul–dump unit maneuverability when electric tethered machines are used. The proposed methodology could be used with any regularly spaced layout or even performed by optimizing the location of each drawpoint considering constraints; however, optimizing each drawpoint would require extensive CPU time and significantly increase the complexity of the optimization problem.

Three layouts are selected for the purpose of the study. These layouts were chosen based on a previous sensitivity analysis. Table 2 shows the three main layouts that are used in this work. Their names are related to the drawpoint spacing across the major and minor pillars (A and B respectively in Fig 8). It is important to mention that the distance between drawpoints within the same bell is 10 m.

Table 1. Relevant mining parameters and assumptions used within Geovia PCBC (Ahmed et al. 2014; Diering 2000, 2013; Laubscher 1994, 2000)

Parameters and assumptions	**Value**	**Unit**	**Description**
% of fines	30	%	Based on a model of fines
Density	2.5	kg/cm^3	Average density for the domains
HIZ	100	m	Height for interaction zone
Swell factor	1.2	–	Stablished by experience
HOD_MAX	500	m	Maximum height of development
HOD_MIN	30	m	Minimum height of development
Initial elevation	1,150	m	Initial elevation of extraction
Radius of draw cone	5	m	Based on fragment sizes
Layout type	–	–	Herringbone

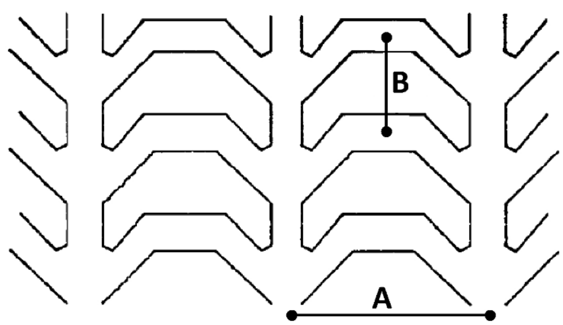


Fig 8. A typical herringbone layout (Chitombo 2010)

Table 2. Three of the drawpoint layouts used to find the optimal NPV

Layout name	**A (m)**	**B (m)**
20 × 10	20	10
20 × 15	20	15
20 × 20	20	20

In addition to the layout, values such as rock density and percent of fines are also required. The average fragment size, where the rock is moderately fractured, is assumed to range from 0.5 to 1 m^3. Consequently, the radius of the draw cones is set to 5 m. The initial level of extraction is assumed to be 1,150 m using PCBC's Footprint Finder; however, this is optimized after the layout of the drawpoints is considered.

The development cost for each layout configuration is shown in Fig 9. This cost depends on the number of drawpoints in the layout. The number of drawpoints and the distance between them are critical factors that help calibrate the amount of dilution without losing ore production while also minimizing development cost. For example, the total development cost increases when the chosen configuration has a large number of drawpoints.

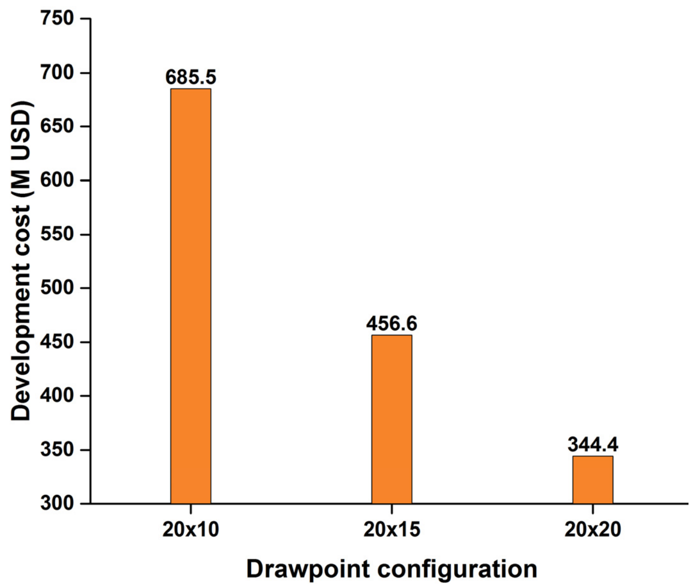


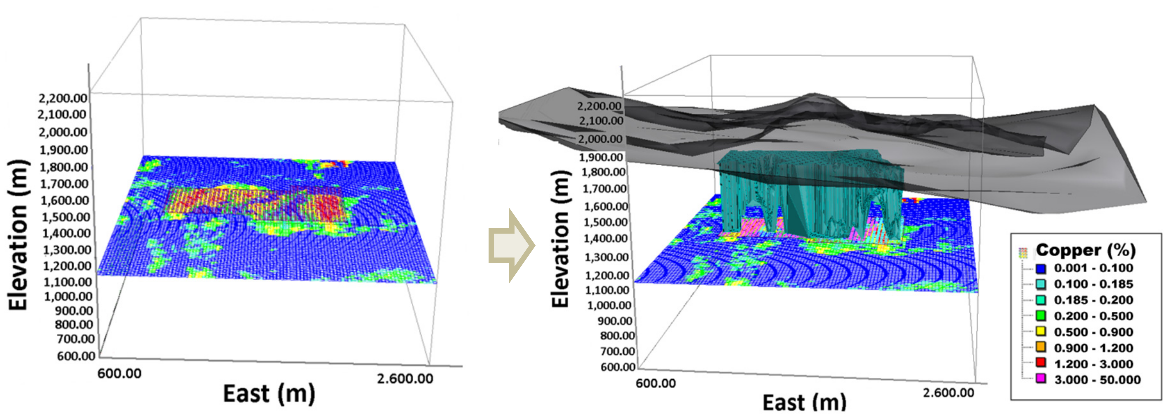
Fig 9. The total development cost for the three extraction layouts

2.3. Optimization of drawpoint layout

For each of the chosen drawpoint configurations, the NPV is determined using PCBC for each of the 40 realizations. Fig 10 illustrates one of these realizations with the 20 × 15 layout. The final results of tonnage, grade and NPV are shown in Table 3 and Fig 11.

Usually, the maximum NPV average is preferred (20 × 15 layout Table 3), but using the proposed technique the uncertainty in NPV can be quantified. The 20 × 15 layout corresponds to a distribution of NPV values (Fig 12) and this uncertainty can be used to better evaluate potential decisions made in the mining process.

The maximum average NPV is usually desired but the layout with the smallest risk, measured by the variance of the NPV, could also be selected for very risk adverse practitioners (20 × 20 layout Table 3). Moreover, if the highest tonnage or %Cu is desired, layout 20 × 10 may be preferred; note that this layout preforms poorly as measured by NPV because of the high development cost.



(a) (b)

Fig 10. Calculation of minable reserves by PCBC. (a) SGS realizations with 20 × 15 drawpoint layout shown; and, (b) topography and caved blocks overlain on the SGS realization

Table 3 Summary of tonnage, grade and net value for 40 realizations

Configuration	Minimum	Maximum	Average
Tonnage (Mtonne)			
20 × 10	**234**	**315**	**285**
20 × 15	220	267	249
20 × 20	184	221	207
Grade (%Cu)			
20 × 10	**0.68**	**0.78**	**0.72**
20 × 15	0.60	0.69	0.65
20 × 20	0.55	0.65	0.61
NPV (M USD)			
20 × 10	919	1,998	1,516
20 × 15	**1,530**	**2,384**	**2,046**
20 × 20	1,581	2,256	1,989

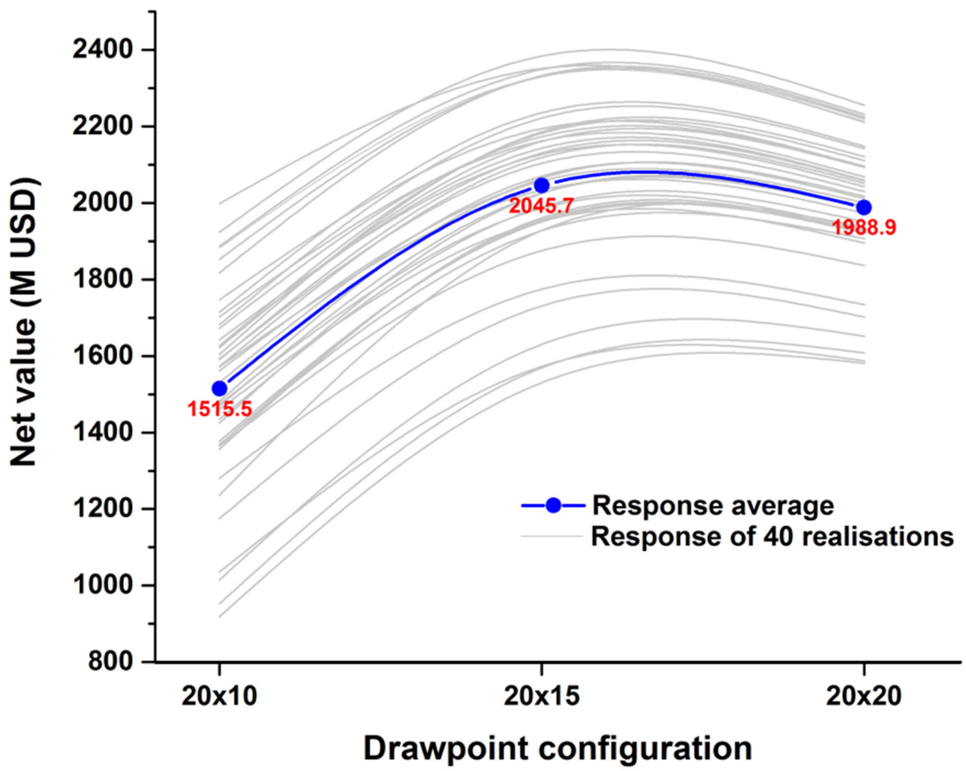


Fig 11. The grey thin curves represent the responses (NPV) of 40 stochastic realizations. The thick blue line represents the average result. Note values are extrapolated between each of the three tested layouts

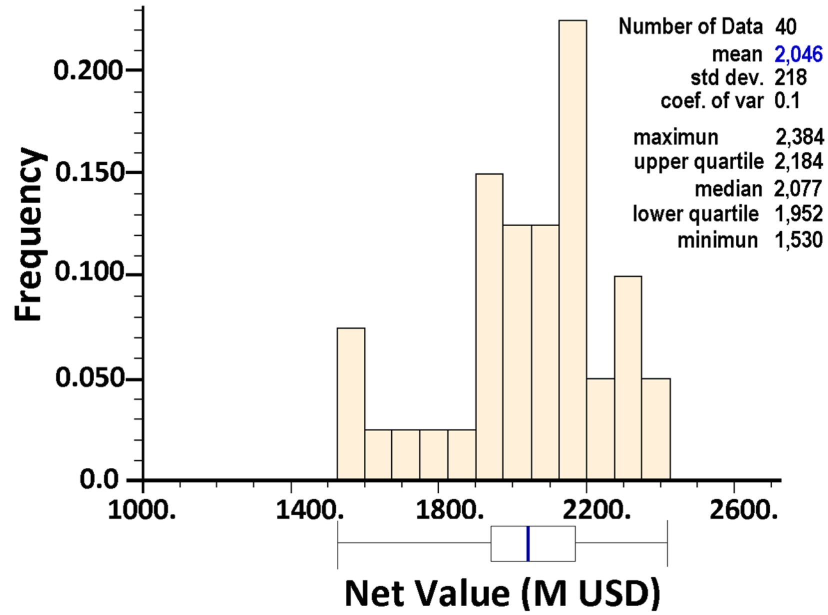


Fig 12. Distribution of net values for the 20 × 15 layout. The mean is USD 2,046 M

As mentioned previously, the total development cost depends on the number of drawpoints. When drawpoints are closer, development is expensive and dilution may increase, but tonnage recovered is also high. Increasing drawpoint spacing can reduce profit due to ore lost. Fig 13 shows that the 20 × 15 layout increase profit, reaching an average NPV of USD 2,046 M.

The optimal layout could be further refined by assessing additional layouts between 20 × 20 and 20 × 10, such as 20 × 17.5 or 20 × 12.5. This type of binary search can be repeated until the user is satisfied with the level of precision in the optimization.

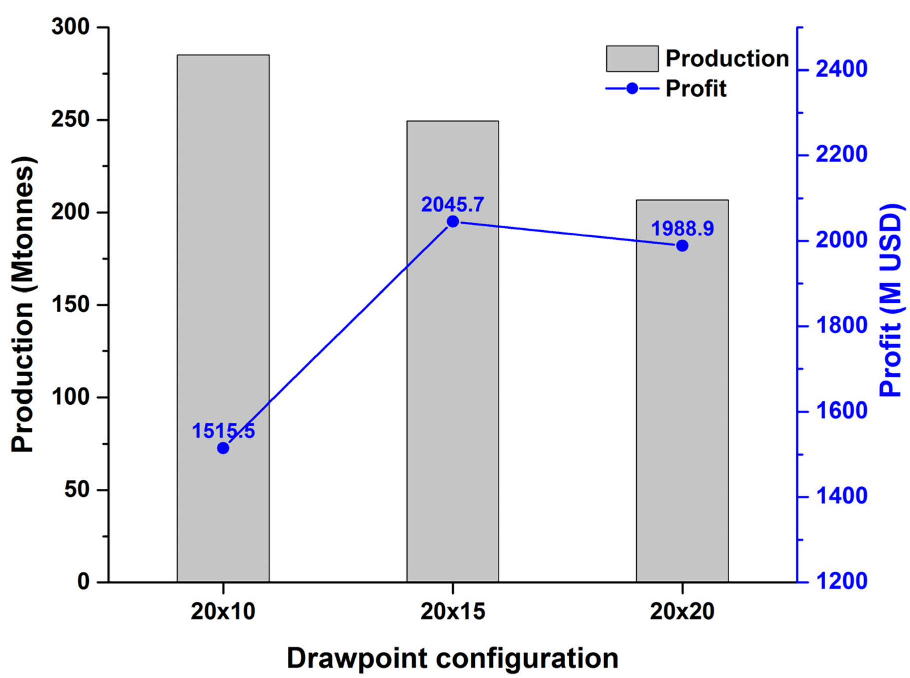


Fig 13. Production tonnage and profit for different configurations

2.4. Optimization of the extraction level

Once the optimum layout is known, the extraction level can be optimized. Four levels: 1,030, 1,090, 1,150, and 1,180 m were selected and the NPV of each of the 40 realizations are determined using a 20 × 15 layout. The calculation of NPV with PCBC at the four proposed levels of extraction show that the maximum average NPV is achieved at the 1,150 m level (Fig 14). As with the layout optimization, further refinement could be made by testing the 1,065 m and 1,120 m level.

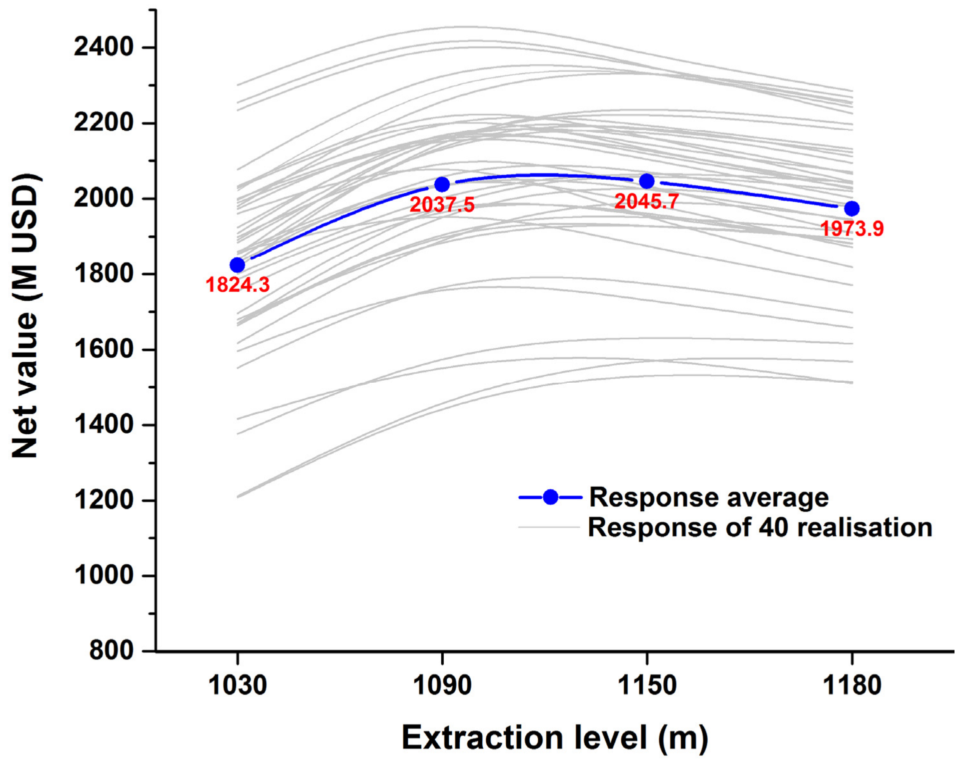


Fig 14. The grey thin curves represent the responses (NPV) of 40 stochastic realizations. The thick blue line represents the average result. Note values are extrapolated between each of the four tested layouts

Additional optimization steps could be performed iteratively. In this study, the layout is optimized followed by the extraction level. With the new extraction level, the optimal layout could be revaluated using the same procedure described in Section 2.4. With this new optimal layout, the optimal extraction level could be revaluated as in Section 2.5. This could be repeated until the practitioner is satisfied with the result, successive iterations would eventually converge on the optimal value for the mine and the user must define their level of tolerance (usually based on the block size). It is important to mention that further parameter analysis will be conducted to measure the influence of dilution, fragmentation, and rock quality for improving this approach.

3. Conclusion

This paper provides an approach for using a set of stochastic realizations to solve a practical engineering concern in block caving. The proposed methodology optimizes drawpoint spacing over multiple geostatistical realizations rather than simply using geostatistical realizations in a post-processing framework to assess a layout based on a kriged model.

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An application of mathematical programming and sequential Gaussian simulation for block cave production scheduling

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ABSTRACT

The current trend of deeper and lower-grade deposits makes open pit mining less profitable. Mass mining alternatives have to be developed if mining at a similar rate has to be continued. Block cave mining is becoming an increasingly popular mass mining method, especially for large copper deposits currently being mined by open pit methods. After finding the initial evaluation of a range of levels for starting the extraction of block cave mining, production scheduling plays a key role in the entire project's profitability. The traditional long-term mine planning is based on deterministic orebody models, which can ignore the uncertainty in the geological resources. The purpose of this paper is to present a methodology to find the optimal extraction horizon and sequence of extraction for that horizon under grade uncertainty. The model does not explicitly take into account other potential project values drivers such as waste ingress into the draw column or the impact of primary or secondary fragmentation on either production or recovery. Maximum net present value (NPV) is determined using a mixed-integer linear programming (MILP) model after choosing the optimum horizon of extraction given some constraints such as mining capacity, production grade, extraction rate and precedence. Application of the method for block-cave production scheduling using a case study over 15 periods is presented.

1. Introduction

Among the underground mining methods available, caving methods are favoured because of their low operational costs and high production rates. Production scheduling in block caving, because of its significant impact on the project's value, has been considered a key issue to be improved. To that end, researchers have applied different methods such as mathematical programming to model production scheduling in block caving (Chanda 1990; Diering 2004, 2012; Epstein et al. 2012; Guest et al. 2000; Khodayari & Pourrahimian 2014, 2015a, 2016; Parkinson 2012; Pourrahimian 2013; Pourrahimian & Askari-Nasab 2014; Pourrahimian et al. 2013; Rahal et al. 2008; Rubio 2002; Rubio & Diering 2004; Smoljanovic et al. 2011; Song 1989; Weintraub et al. 2008).

These models are built to help the decision-maker evaluate the consequences of various management alternatives. In order to be most useful, the decision support model should also include information about the uncertainties related to each of the decision options, as the certainty of the desired outcome may be the central criterion for the selection of the management policy.

Ore grade is one of the crucial parameters subject to uncertainty in mining operations. Grade uncertainty can lead to significant differences between actual production outcomes and planning expectations and, as

This paper, in its entirety, has been submitted for publication in the 1st International conference in Underground Mining Technology (UMT2017).

a result, the net present value (NPV) and internal rate of return (IRR) of the project (Koushavand & Askari-Nasab 2009; Osanloo et al. 2008). Various researchers have considered the effects of grade uncertainty in open pit mines and introduced different methodologies to address those effects (Albor & Dimitrakopoulos 2009; Asad & Dimitrakopoulos 2013; Dimitrakopoulos & Ramazan 2008; Dowd 1994; Koushavand & Askari-Nasab 2009; Lamghari & Dimitrakopoulos 2012; Lamghari et al. 2013; Leite & Dimitrakopoulos 2007; Maleki & Emery 2015; Ramazan & Dimitrakopoulos 2004, 2013; Ravenscroft 1992; Sabour & Dimitrakopoulos 2011).

Other than the aforementioned authors, few authors have examined geological uncertainty in underground mining. Grieco and Dimitrakopoulos (2007) implemented a new probabilistic mixed-integer programming model which optimizes the stope designs in sublevel caving. Vargas et al. (2014) developed a tool that considered geological uncertainty by using a set of conditional simulations of the mineral grades and defining the economic envelope in a massive underground mine. Montiel et al. (2015) incorporated geological uncertainty into their methodology that optimizes mining operation factors such as blending, processing, and transportation. They used a simulated annealing algorithm to deal with uncertainty. Carpentier et al. (2016) introduced an optimization formulation that looked at a group of underground mines under geological uncertainty. Their formulation evaluates the project's influence on economic parameters including capital investments and operational costs.

One of the main steps involved in optimizing underground mines is determining a cut-off grade and its associated mining outline and contained mineral inventory. The open pit corollary to this is open pit optimization, which is completed with algorithms such as those by Lerchs and Grossmann (1965).

To optimize block caving scheduling, most researchers have used mathematical programming: linear programming (LP), mixed-integer linear programming (MILP), quadratic programming (QP), mixed-integer quadratic programming (MIQP), and mixed-integer linear goal programming (MILGP) (Chanda 1990; Diering 2004, 2012; Epstein et al. 2012; Guest et al. 2000; Khodayari & Pourrahimian 2014, 2015a, 2016; Parkinson 2012; Pourrahimian 2013; Pourrahimian & Askari-Nasab 2014; Pourrahimian et al. 2013; Rahal et al. 2008; Rubio 2002; Rubio & Diering 2004; Smoljanovic et al. 2011; Song 1989; Weintraub et al. 2008). Khodayari and Pourrahimian (2015b) presented a comprehensive review of operations research in block caving.

This paper will introduce a method designed to identify the optimal horizon for initializing extraction according to the maximum discounted ore profit under grade uncertainty. The model does not explicitly take into account other potential project values drivers such as waste ingress into the draw column or the impact of primary or secondary fragmentation on either production or recovery. Several realizations are modelled by using geostatistical studies to consider grade uncertainty. The production schedule is generated for the given advancement direction and in the presence of constraints such as mining capacity, grade of production, reserve, precedence, and number of active blocks at the chosen level.

2. Methodology

The orebody is represented by a geological block model. Numerical data are used to represent each block's attributes, such as tonnage, density, grade, rock type, elevation, and economic value.

The first step is to construct a block model based on the drillhole data and the grid definition. The next step is a geostatistical study to generate the realizations. Then, the optimal extraction horizon is identified for each realization. Finally, the optimal sequence of extraction is determined to maximize the NPV.

2.1. Geological uncertainty

The first step for a geostatistical study is to define different rock types based on the drillhole data. In this study, which assumes a stationary domain within each rock type, the geostatistical modelling is performed for each rock type separately. The following steps are common for generating a geological model: First, a de-clustering algorithm is used to get the representative distribution of each rock type to decrease the weight of clustered samples. Then, the correlation of the multivariate data is determined. To determine the principle directions of continuity, global kriging is performed using arbitrary variograms with a high range. Indicator kriging is used for rock type modelling, and simple kriging is used for grade modelling. The data is transformed to Gaussian units to remove the correlation between the variables in each rock type.

The experimental variograms are calculated by using the determined directions of continuity in the previous step and a model is fitted to these variograms in different directions. An indicator variogram is used for rock type modeling and a traditional variogram is used for grade modeling. A rock type model is generated for the chosen grid definition by using a sequential indicator simulation algorithm (SIS). A grade model for each rock type is generated based on a sequential Gaussian simulation algorithm (SGS). Then, the data is back-transformed to original units. Finally, grade modeling is done within each rock type.

2.2. Placement of extraction level

To find the optimum horizon of extraction, the ore tonnage and discounted profit are calculated for each level of the block model. The discounted profit of each ore block (Diering et al. 2008) and the total discounted profit of each level are calculated using Equations 1 and 2. Then the tonnage–profit curve is plotted and the level with the highest profit is selected for starting the extraction.

$$Dis\,\mathrm{P}_{blL} = \frac{\mathrm{Pr}}{(1+i)^{d/ER}} \tag{1}$$

$$Dis\,\mathrm{P}_{L} = \sum_{bl=1}^{BL} Dis\,\mathrm{P}_{blL} \tag{2}$$

where:

$Dis\ P_{blL}$ is the discounted profit of ore block bl in level L and the above blocks, $Dis\ PL$ is the total discounted profit of level L, Pr is the profit of ore block bl and ore blocks above it, i is the discount rate, d is the distance between the centre points of ore block bl in level L and the ore blocks above it, ER is the extraction rate per period, and BL is the total number of ore blocks in level L.

After determining the optimal elevation, the interior of the orebody outline is divided into rectangles based on the required minimum mining footprint. The minimum mining footprint represents the minimum sized shape that will induce and sustain caving in the overlying rock. This is equivalent to the hydraulic radius in a caving operation. Then all blocks inside of the rectangle and above that creates big-blocks. In the next step, the sequence of extraction of these big-blocks is optimized using an MILP model (Fig 1).

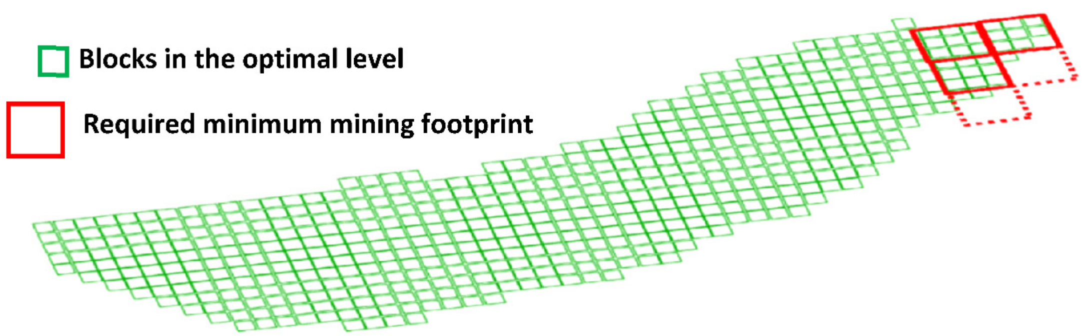

Fig 1. Dividing the interior of orebody into rectangles based on the required minimum mining footprint

The MILP model is developed in MATLAB , and solved in the IBM ILOG CPLEX environment (IBM 2015). A branch-and-bound algorithm is used to solve the MILP model, assuring an optimal solution if the algorithm is run to completion. A gap tolerance (EPGAP) is used as an optimization termination criterion. This is an absolute tolerance between the gap of the best integer objective and the objective of the remained best node.

3. Mathematical formulation

The notation of sets, indices and decision variables for the MILP model are as follows (Table 1):

Table 1. Decision variables, set, indices, and parameters of the MILP model

Indices	
$t \in \{1,....,T\}$	Index for scheduling periods.
$bl \in \{1,...,BL\}$	Index for small-blocks.
$bbl \in \{1,...,BBL\}$	Index for big-blocks.
Set	
S^{bbl}	For each big-block, *bbl* , there is a set S^{bbl}, which define the predecessor big-blocks that must be started prior to extracting the big-block *bbl*.
Decision variables	
$B_{bbl,t} \in \{0,1\}$	Binary variable controlling the precedence of the extraction of big-blocks. It is equal to one if the extraction of big-block *bbl* has started by or in period *t*; otherwise, it is zero.
$x_{bbl,t} \in [0,1]$	Continuous variable, representing the portion of big-block *bbl* to be extracted in period *t*.
$y_{bbl,t} \in \{0,1\}$	Binary variable used for activating either of two constraints.
Parameters	
$Profit_{bbl}$	Profit of big-block *bbl*.
Ton_{bbl}	Tonnage of big-block *bbl*.
$MCL\,(Mt)$	Lower bound of mining capacity.
$MCU\,(Mt)$	Upper bound of mining capacity.
g_{bbl}	Average grade of the element to be studied in big-block *bbl.*
$GL\,(\%)$	Lower bound of the acceptable average head grade of considered element.
$GU\,(\%)$	Upper bound of the acceptable average head grade of considered element.
$ExtU\,(Mt)$	Maximum possible extraction rate from each big-block.
$ExtL\,(Mt)$	Minimum possible extraction rate from each big-block.
L	Arbitrary big number.
T	Maximum number of scheduling periods.
BBL	Number of ore big-blocks in the model.
n	Number of predecessor big-blocks of big-block *bbl.*
$\overline{N}_{NBBL,t}$	Upper bound for the number of new big-blocks, the extraction from which can start in period *t*.
$\underline{N}_{NBBL,t}$	Lower bound for the number of new big-blocks, the extraction from which can start in period *t*.

3.1. Objective function and constraints

3.1.1. Objective function

The objective function of the MILP formulation is to maximize the NPV of the mining operation, which depends on the value of the big-blocks. The objective function, Equation 3, is composed of the big-blocks' profit value, discount rate, and a continuous decision variable that indicates the portion of a big-block, which is extracted in each period. The most profitable big-blocks will be chosen to be part of the production in order to maximize the NPV.

$$Max \quad \sum_{t=1}^{T} \sum_{bbl=1}^{BBL} \frac{Profit_{bbl} \times x_{bbl,t}}{(1+i)^t} \tag{3}$$

3.1.2. Constraints

- *Mining capacity*

These constraints ensure that the total tonnage of material extracted from each big-block in each period is within the acceptable range. The constraints are controlled by the continuous variables.

$$MCL_t \leq \sum_{bbl=1}^{BBL} Ton_{bbl} \times x_{bbl,t} \leq MCU_t \tag{4}$$

- *Grade of production*

These constraints ensure that the production's average grade is in the acceptable range.

$$GL_t \leq \frac{\sum_{bbl=1}^{BBL} g_{bbl} \times Ton_{bbl} \times x_{bbl,t}}{\sum_{bbl=1}^{BBL} Ton_{bbl} \times x_{bbl,t}} \leq GU_t \tag{5}$$

- *Block extraction rate and continuous extraction*

Equation 6 ensures that the extraction rate from each big-block per period does not exceed the maximum extraction rate. $y_{bbl,t}$ in Equation 7 and 8 is a binary variable which is used to activate either Equation 7 or 8. Whenever Equation 7 is active, it ensures that minimum extraction rate from each big-block per period is extracted. If the remaining tonnage of a big-block is less than the minimum extraction rate, Equation 8 will be activated and forces that big-block to be extracted as much as the remaining tonnage which results in continuous extraction from each big-block.

$$Ton_{bbl} \times x_{bbl,t} \leq ExtU_{bbl,t} \tag{6}$$

$$(ExtL_{bbl,t} \times B_{bbl,t}) - (Ton_{bbl} \times x_{bbl,t}) \leq L \times y_{bbl,t} \tag{7}$$

$$\sum_{t'=1}^{t} x_{bbl,t} \geq y_{bbl,t} \tag{8}$$

- *Binary constraints*

Equation 9 ensures that if the extraction of one big-block is started its binary variable should be one. Also, Equation 10 controls the fact that if the extraction of one big-block in period t has been started ($B_{bbl,t} = 1$), the related binary variable should be kept one till end of the mine life. Both Equation 8 and 10 contribute to the continuity of the extraction. The results of these constraints will be used for the precedence constraint for which the maximum number of active big-blocks is needed.

$$x_{bbl,t} \le B_{bbl,t} \tag{9}$$

$$B_{bbl,t} - B_{bbl,t+1} \le 0 \tag{10}$$

- *Number of new big-blocks*

Equation 11 and 12 ensure that the number of new big-blocks in each period should be in an acceptable range. It is obvious that the number of new drawpoints in period one is more than other periods; therefore Equation 11 is applied to period one and Equation 12 is applied from period two to the end of the mine's life.

$$\underline{N}_{NBBL,1} \le \sum_{bbl=1}^{BBL} B_{bbl,t} \le \overline{N}_{NBBL,1} \tag{11}$$

$$\underline{N}_{NBBL,t} \le \sum_{bbl=1}^{BBL} B_{bbl,t} - \sum_{bbl=1}^{BBL} B_{bbl,t-1} \le \overline{N}_{NBBL,t} \tag{12}$$

- *Precedence*

Equation 13 ensures that all the predecessor big-blocks of a given big-block *bbl* have been started prior to extracting this big-block.

$$n \times B_{bbl,t} \le \sum_{k=0}^{n} B_{S^{bbl}(k),t} \tag{13}$$

- *Reserve*

In this formulation, all material inside of the big-blocks should be extracted. This is controlled by Equation 14.

$$\sum_{t=1}^{T} x_{bbl,t} = 1 \tag{14}$$

4. Case study

4.1. Grade uncertainty

A geostatistical study based on the drillhole data of a copper deposit was performed and a block model constructed. Geostatistical software library (GSLIB) (Deutsch & Journel 1998) was used for geostatistical modelling in this paper. The initial inspection of the locations of the drillholes showed that the drillholes were equally spaced. As a result, the de-clustering algorithm was not implemented. There were two parts to the modelling: rock type modelling and grade modelling. The grade modelling was implemented for both rock types (ore and waste) separately.

4.1.1. Rock type modeling

The principal directions of continuity were found using indicator kriging. Afterwards, the indicator variograms were calculated and a theoretical variogram model was fitted with three structures. In Fig 2, the top left shows the plan view of the maximum direction of continuity for rock types at Elevation 40 and experimental directional variograms (dots) and the fitted variogram models (solid lines) for rock type and distance units in meters. At the next step, 20 realizations for rock types were generated using a sequential indicator simulation algorithm (SIS) algorithm. A plan view of the rock type simulation for the first realization at Elevation 40 is shown in Fig 2 (top right).

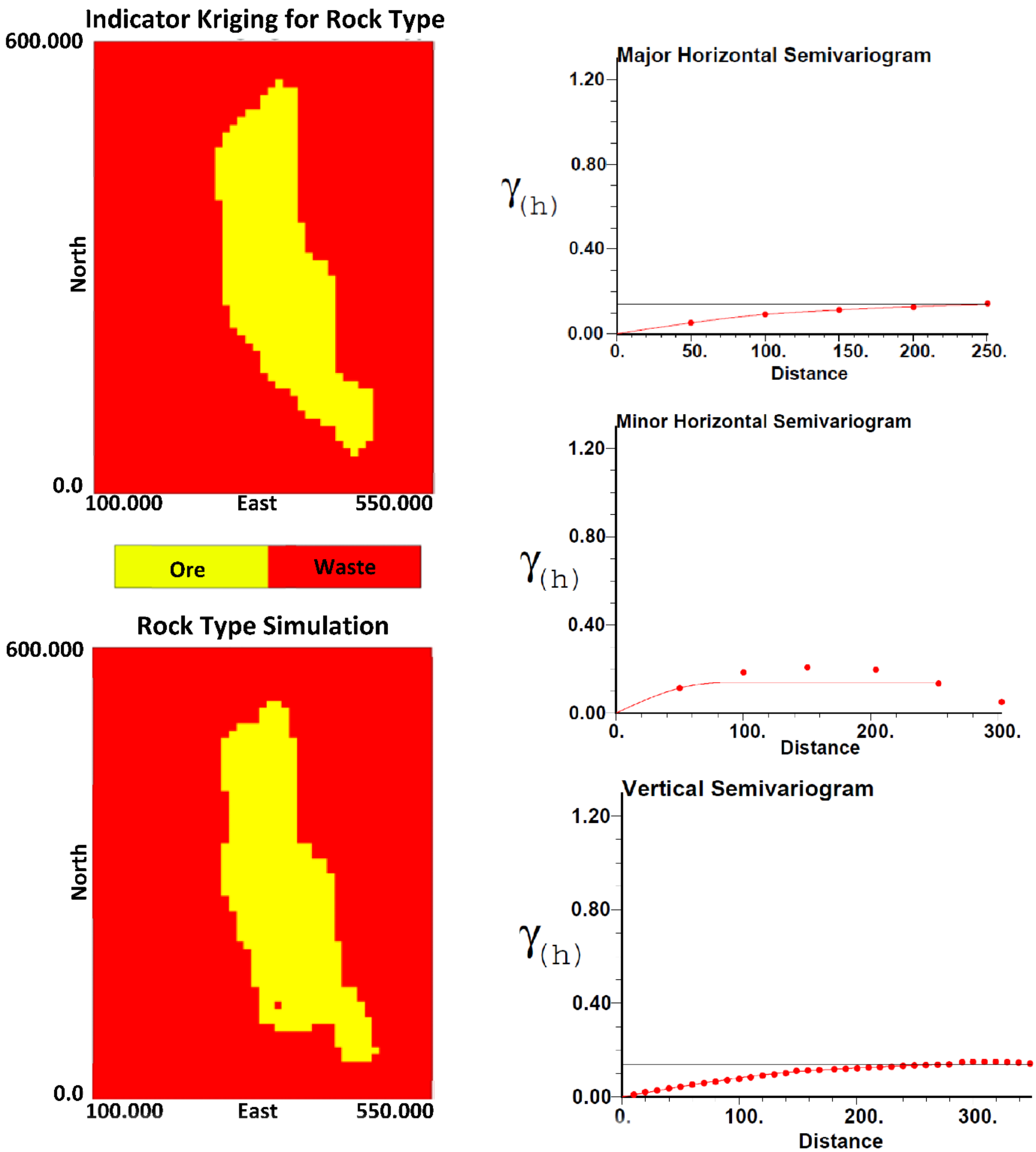

Fig 2. Dividing rock type modelling and simulation

4.1.2. Grade modeling

For ore modelling, the principal directions of continuity were extracted by doing simple kriging with the help of arbitrary variograms. Then the copper grades were transformed to Gaussian space. In Fig 3, the top left shows a plan view of the maximum direction of continuity for the copper grade at Elevation 40.

Traditional variogram calculation and modelling with three structures and a nugget effect of 0.1 was done for the copper grade. Afterwards, 20 realizations for the copper grade were generated using SGS algorithms. The SGS needs a back-transformation to original units. The plan view of copper grade simulation for the first realization at Elevation 40 is shown in Fig 3 (top right).

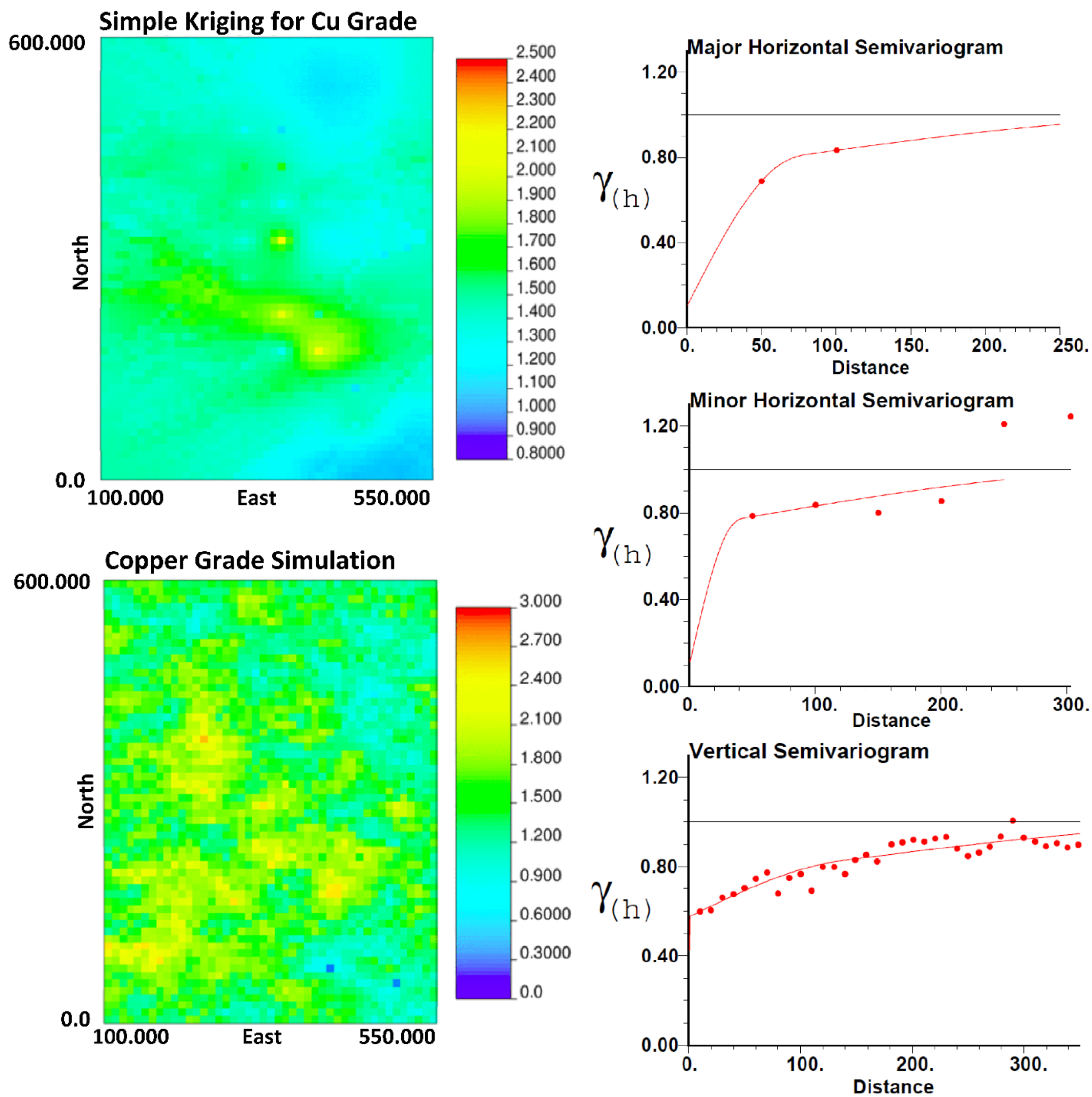

Fig 3. Grade modelling and simulation

The next step was to match and merge the rock type model with the grade model for each realization. Fig 4 shows the plan view of the final simulation for the first realization. Fig 5 shows the variogram reproduction of the rock property (ore) simulation (top) and rock type simulation (bottom) in three major, minor, and vertical directions. Since the variograms were reproduced quite reasonably, the generated realizations were considered representative of the grade uncertainty.

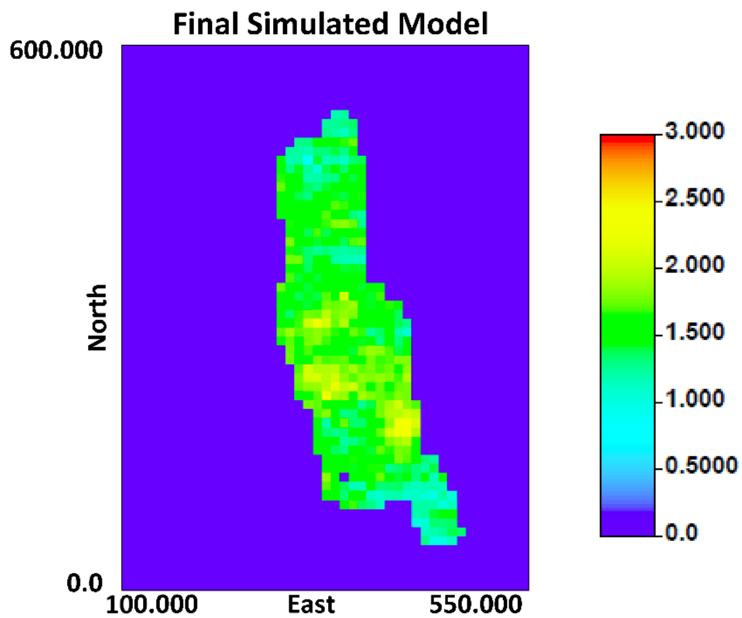

Fig 4. Final simulation of the first realization at Elevation 40

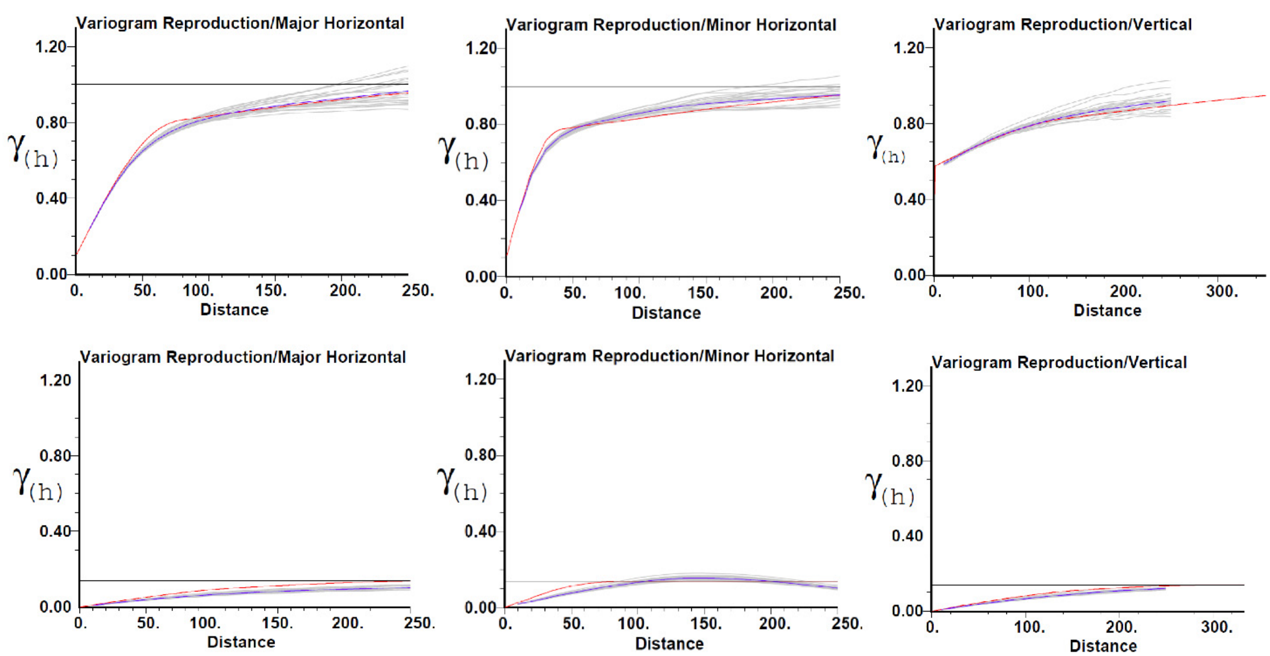

Fig 5. Variogram reproduction at Gaussian units of copper grade (top) and rock type (bottom) realizations (grey lines), the reference variogram model (red line), and the average variogram from realizations (blue line) in three directions

4.2. Placement of extraction level

The discounted profit and tonnage of the ore blocks above each ore block in each level were calculated (Equation 1 and 2) and the profit–tonnage curve was plotted for the original model (single estimated orebody model) and all realizations. The discounted profit was calculated for the block height of 10 m and the vertical extraction rate of 15 (meters/period). This led to selecting the optimal horizon for starting extraction based on maximum profit for each realization. Fig 6 shows an example of the tonnage–profit curve for one of the realizations and the histogram of the obtained extraction levels for realizations.

The extraction horizon varies between level 34 and 40. In 40% of the realizations, level 39 is the optimum level of extraction from a NPV perspective. In addition to the realizations, a single block model was also considered. In this block model (original model), the grade estimation was done using kriging technique. It should be noted that the optimum level of extraction for the original model was level 38 which was identified in 20% of the realizations.

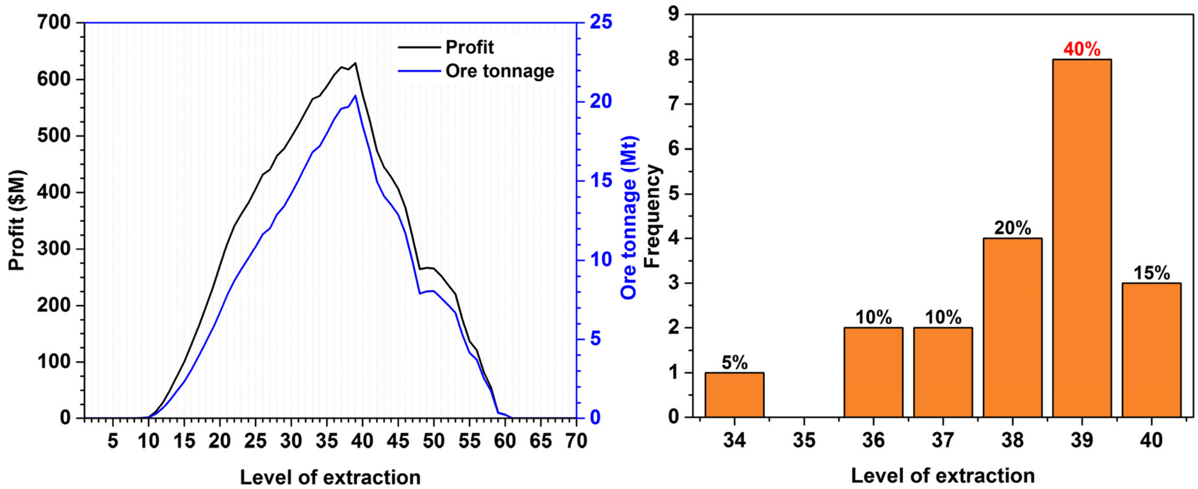

Fig 6. Selection of optimal extraction horizon based on tonnage–profit curve (left, one realization) and histogram of the optimum level of extraction for realizations

After determining the optimal extraction horizon an optimal advancement direction was selected using the method presented by Khodayari and Pourrahimian (2015a). Then, because of the distances between drawpoints and the assumed footprint size (30 × 30 m), the blocks were placed into bigger blocks along the advancement direction. Additionally, as the big-blocks close to the boundaries did not constitute a complete set (with nine small blocks), only sets with seven or more blocks were considered. Fig 7 shows the steps from finding the extraction level to creating the big-blocks.

4.3. Production scheduling

In order to evaluate the risks due to the presence of grade uncertainty, the changes in NPV and tonnage should be investigated. Considering the deterministic values for the grade, original block model results in one NPV or tonnage at the end. Optimization of the production schedule based on kriging will not assess uncertainty and will thus be suboptimal. To maximize the calculated NPV, the proposed mathematical model was applied to generate the production schedule for the original block model and realizations. Table 2 shows the scheduling parameters for the MILP model.

Results of the original model are presented here to show that all the constraints have been satisfied. The original model had 90 big-block columns. Fig 8 shows the production grade and tonnage in each period for the optimum level of extraction in the original model. The amount of extracted ore was 37.5 Mt with an NPV of USD 1,010 M. Fig 8 shows that the maximum mining capacity is reached from period one to period 10, then production decreases gradually until the end of the life of mine. It should be noted that in the solved example, ramp-up period has not been defined in the scheduling parameters. The grade of production increases gradually during the first nine periods and the material with higher grades is extracted at first and then it decreases slowly.

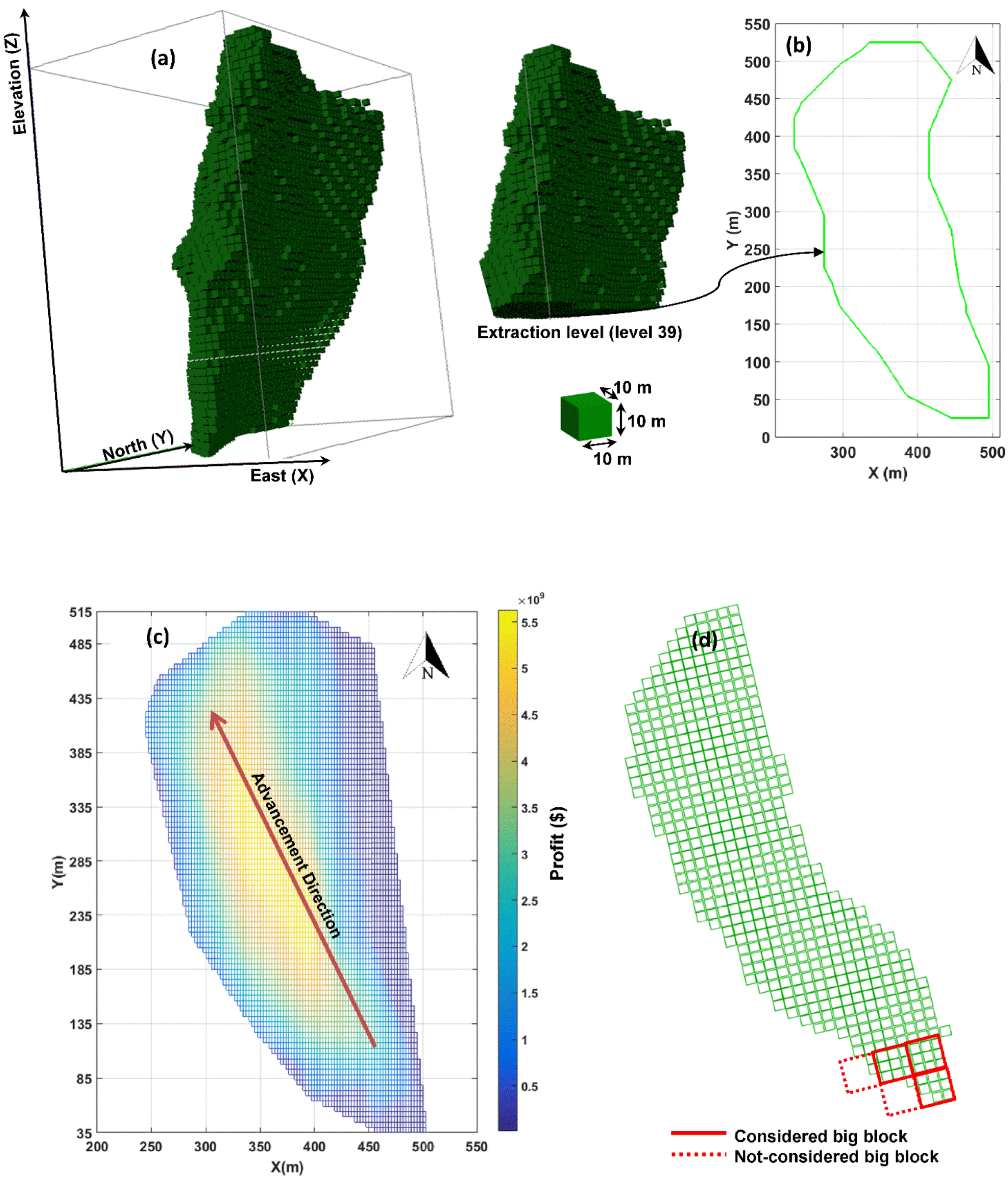

Fig 7. (a) block model of the orebody, (b) outline of the orebody at level 39, (c) optimum advancement direction based on the profit at the considered level (Khodayari & Pourrahimian 2015a); and, (d) schematic view of considering big-blocks with more than seven small blocks

Table 2. Scheduling parameters for MILP model (original and realizations)

Parameter	Value	Parameter	Value
T (Period)	15	i (%)	10
MCL (tonne)	1,200,000	Recovery (%)	85
MCU (tonne)	3,000,000	$\overline{N}_{NBBL,1}$	28
GL (%)	1.3	$\underline{N}_{NBBL,1}$	0
GU (%)	1.6	$\overline{N}_{NBBL,t}$	5
ExtL (tonne)	90,000	$\underline{N}_{NBBL,t}$	2
ExtU (tonne)	350,000	L	100,000,000

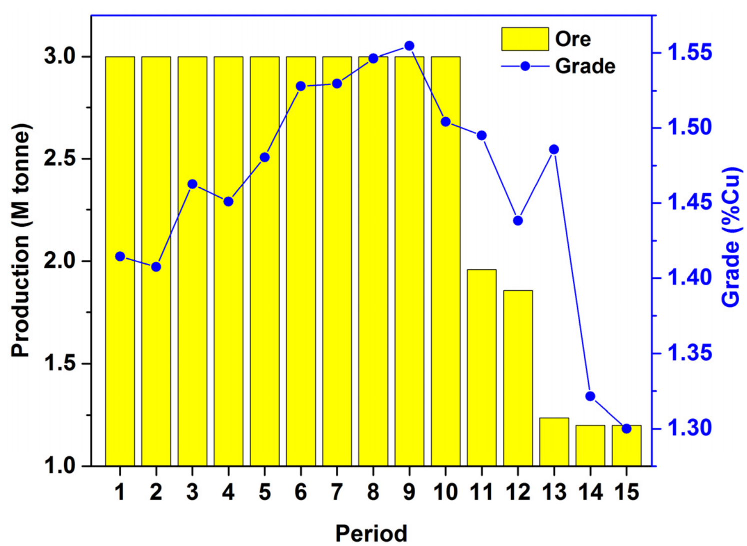

Fig 8. Ore production tonnage and average grade over the life of mine (original model)

Fig 9 shows the number of active and new big-blocks should be opened in each period. The formulation tries to open more big-blocks at period one in order to maximize the NPV and because of that, 27 big-blocks were opened at period one.

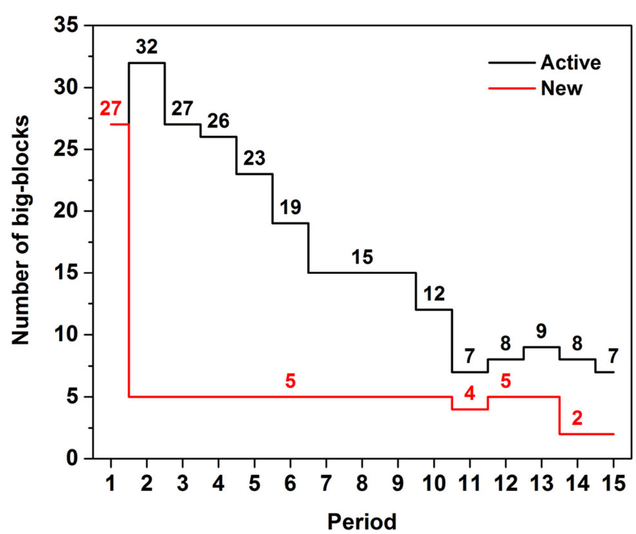

Fig 9. Number of active and new big-blocks for each period over the life of the mine (original model)

Fig 10 shows the frequency of NPV and production tonnage for all the realizations at their own optimum extraction horizon. As it can be seen, the NPV varies between USD 965 M and USD 1,086 M and the mean was USD 1,026 M. The minimum and maximum ore tonnages that can be extracted were 33.2 and 39.6 Mt, respectively. The original block model's tonnage and NPV values were within the lower and upper quartile.

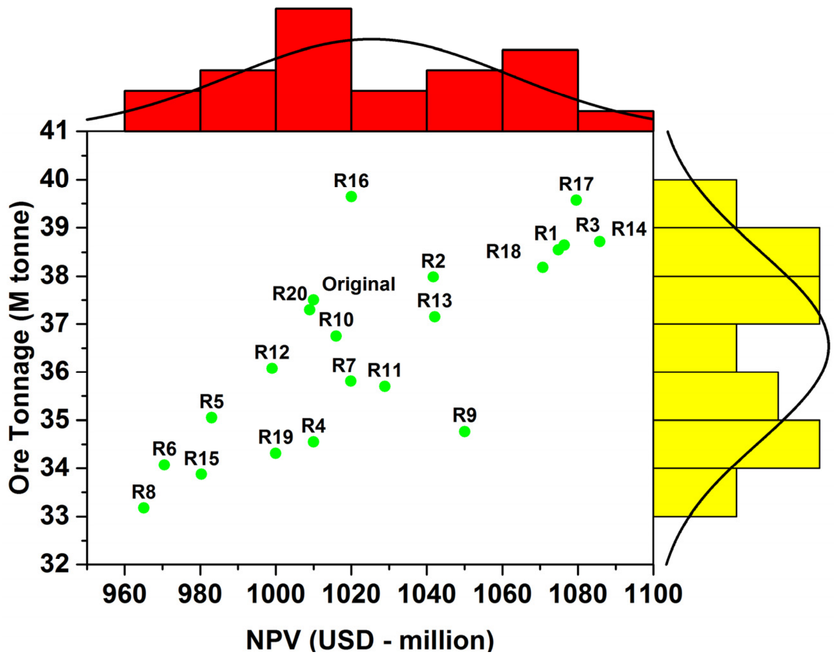

Fig 10. Histogram of NPV and extracted ore tonnage for realizations and the original model

5. Conclusion

Grade uncertainty has been used in open pit mining but is less studied in underground mining, especially in block caving. Typically, once a block cave is initiated it is difficult modify the NPV and IRR as geometric alterations to the production horizon are difficult to implement.

This paper considers grade uncertainty and presents a methodology to identify the first pass optimal extraction horizon for block cave mining. Ignoring the grade uncertainty during the production scheduling can cause an optimistic schedule. The majority of block caving mines use kriging as the main technique to estimate resources. Therefore, the block model generated in kriging is used to identify the optimum horizon of extraction. There are a number of drawbacks, including (i) only a single response can be calculated (i.e. a single NPV), (ii) it is difficult to assess uncertainty in the response (i.e. NPV, tonnes per year, dilution, production rate, etc.), and (iii) the impact of the smoothing effect of kriging is difficult to quantify.

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Determination of Optimal Underground Stope Layout

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ABSTRACT

Stope layout optimization means determining the best dimension and the locations of the stopes and number of stopes. Stope layout in underground mining directly affects other significant aspects of mining such as economic value and mining recovery. Compare to the open-pit mine, limited techniques and algorithms are available to find the optimums in designing underground mine, and most of those fail to provide an exact optimum solution especially in 3D space.

The goal of this research is creating a stope optimizer algorithm to find the best combination of the stops with highest economic value. In fact, this research directly contributes to creating a new heuristic model which can tackle the complexity of stope layout designing and at the same time can achieve to the near-optimal solution in 3D space.

1. Introduction

According to Canada's Economic Action Plan, the energy and mining sector provides over $30 billion a year in revenue to governments. The economics of today's mining industry is such that the major mining companies are increasing the use of massive underground mining methods. They expect that approximately 50 percent of the world's copper production will come from underground mines by 2020. It is a step change for the industry, from the traditional open-pit to a move underground.

Several algorithms have been presented to optimize the stope layout for underground mining in the last 40 years. Most of the earlier works on stope optimization were based on the strong simplifications of the initial problem (Bai et al., 2013). However, some of those indicated the proper algorithms which achieved the important goals such as maximum economic value, maximum mining recovery, minimum ore dilution and minimum ore loss (Dimitrakopoulos et al., 2009).

An ore reserve model, which defined by a set of small regular blocks, is basic input for stope optimization (David, 1988). In order to find optimum stope layout, geotechnical and operational and economical considerations such as characteristics of the ore body, accessing to stopes, mining equipment size, pillar size to be looked at (Bai et al., 2013; Sandanayake et al., 2015a).

Generally, the all presented 2D or 3D algorithms to define the optimal stope layout classify to two groups of mathematical (exact) and heuristic. Mathematical algorithms are supported by mathematical proof; however, the heuristic algorithms are based on constraints and limitations to find an approximate solution. For instance, introduced algorithms by Riddle (1977), Ovanic et al. (1995), and Bai et al. (2013) are mathematical, and the remains follow the heuristic model (Sandanayake, 2014).

2. Literature Review

The generated algorithms to find the optimum stope layout in underground mining are reviewed in the following section and their applications, methodologies, capabilities and restrictions and their similarities and contrasts are discussed. In addition, the different objective functions and constraints, which are considered in those algorithms, are presented.

The existing algorithms for underground stope layout optimization are classified in two groups: field-oriented and level-oriented. In the field-oriented algorithms, the economic value of each block considered as a constant value and determination of underground mining limit takes place on the entire mining area before dividing the mining area to levels or panels. In contrast, the level-oriented algorithms are applied on a level or panel (Jalali, 2006).

Riddle (1977) presented the first algorithm, called "Dynamic Programming Algorithm" to find optimum stope layout in block-caving mining method. This method solves the 3D problems by using multi-section 2D; north-south sections and east-west sections. Although his algorithm is able to optimize the sections, it fails to find the true optimum stope in three dimensions because it does not consider all necessary constraints.

Dynamic Programming Algorithm assumes a 2D section of blocks with *i* rows and j columns and it is formulated as equation (1).

$$P_{ijo} = M_{i,j} + \mathrm{Max}\left\{P_{i+r,j-1}\right\} \tag{1}$$

Where, $M_{i,j}$ is the cumulative net value of blocks, r is the range indicating adjacent blocks, and P_{ijo} is the profit achieved by mining through the block (row "i" of drawpoint "j" and starting at any level of drawpoint "o ")

At the first step, P_{ij1} is calculated for all blocks. Then, column 1 is eliminated and all P_{ij2} is calculated and it continues to the last column. Result in the last column is equal to the cumulative net value of blocks. Then the calculations for other rows are done, and at the last step, maximum profit is determined (Ataee-Pour, 2000).

Deraisme et al. (1984) used the Downstream Geostatistical Approach to determine optimal stope. This model is the 2D sectional numerical models of the deposit. Mathematical morphology helps this model to consider the stope geometry constraints. This approach has been recommended when because of underground mining constraints restrictions, the linear and nonlinear geostatistics are not able to estimate the mineable reserves.

Generally, the Downstream Geostatistical Approach is based on a combination of conditional simulation with underground mining simulation to compare: selectivity; productivity; and profitability in cut-and-fill and block caving methods. The approach steps included the constructing a numerical model of the deposit at first and then defining the outlines of the mineable ore (Ataee-Pour, 2000).

Cheimanoff et al. (1989) described a heuristic approach with binary-tree division technique, called "Octree Division Approach", to move from geological resources to mineable reserves based on the mining constraints and provides a 3D solution to find optimum stope. In fact, this model is based on removing the non-desired mining blocks to define the minimum stope size.

This model covers two main constraints. First, the geometric constraints which are based on the ore-body geotechnical behavior as well as mining equipment. Second, the economic constraints which are based on the cut-off grade and the mining costs such as access cost and services cost (Ataee-Pour, 2000).

Ovanic et al. (1995) developed “Branch and Bound Technique” to optimize outline of the stope based on the optimizing of starting and ending points within each row of blocks. To find the optimum starting and ending points, they used two piecewise linear functions for each row. In addition, they considered a mixed integer approach, called "Type-Two Special Ordered Sets", to optimize stope boundary. In fact, two separate "Type-Two Special Ordered Sets" are defined as stope boundaries (starting and ending points) variable. As a result, the objective function is determined as the difference between the cumulative values obtained for the stope boundaries. Equation (2) presents the objective function of the method.

$$Maximise SV = \sum_{i=0}^{n} a_i L_i - \sum_{i=0}^{n} a_i T_i \qquad (2)$$

Where, SV is the difference between the cumulative values of starting and ending points, a_i is the cumulative block economic value, L_i is the starting point variable (bounded between 0 and 1), and T_i is the starting point variable (bounded between 0 and 1).

In addition, the constraints are based on the geometric limitations, which impact on the minimum and a maximum size of stopes.

In contrast with previous algorithms, having only regular or uniform shapes blocks and having only whole blocks are not required in “Branch and Bound Technique” algorithm. In other words, blocks shape or size does not effect on the optimization, because the block cumulative value function has been developed in this model. These points are really beneficial in case of existing the geological interpretations in the block model.

Alford (1996) described the "Floating Stope Algorithm", which is similar to the "Moving Cone" method in open-pit limit optimization, to set up the optimal stope boundary. The positive points of the "Floating Stope Algorithm" are simplicity and generality. Simplicity comes from generating a three-dimensional assessment optimization and sensitivity analysis point of view, and generality comes from using not for only certain mining method point of view. Having the heuristic approach and lacks rigorous mathematical is one the disadvantages of this algorithm. In addition, the “Floating Stope Algorithm” doesn’t guarantee to find the true optimum stope.

Regarding the definition of "Floating Stope" term, this technique is based on moving a floating stope shape with minimum stope dimensions, through blocks to locate the stope position. The process of floating the stope shape can be based on the best grade stope shapes or based on the possible stope positions. However, the problem is the possibility of overlapping of the stopes in the final result (Sandanayake et al., 2015a).

The objectives function in this algorithm can be maximizing ore tonnes or minimizing waste, maximizing grade, maximizing the profit. Also, the main constraint is the geometry of the stope. Finally, the volume of the stope and the profit were determined as outputs (Ataee-Pour, 2000).

Ataee-Pour (2000) presented a heuristic algorithm and called it "Maximum Value Neighbourhood" (MVN). This algorithm works on a fixed economic block model of an ore-body to provide a 3D analysis of optimization of the stope boundaries. He defined the neighborhood concept based on the number of mining blocks equivalent to the minimum stope size.

The MVN algorithm has taken benefits from its generality, which allows it to be applied for any underground mining method and its simplicity in both concept and computer implementation.

MVN algorithm locates the best neighborhood of a block to find the best combination of blocks to create the maximum profit, while certain mining and geotechnical constraints are considered. The mining constraints in this algorithm are based on the restrictions which are determined by minimum stope dimensions in three principal directions. In addition, the size of the equipment and necessary spaces for the drilling, blasting, loading, and traffic of personnel are important in defining the minimum stope dimensions. Also, several physical parameters such as geotechnical properties of the ore-body and the surrounding rock, dip, depth, thickness of the ore-body which can affect the proposed underground mining methods are set up as constraints in this algorithm. However, he has not paid attention to the maximum limits of the stope dimensions which from ground control considerations point of view are important. Also, ignoring the shape of the mineable stopes is the problem with this algorithm (Sandanayake et al., 2015a).

FORTRAN programming language has been used to develop his study. The following stages for optimization process have been described by Ataee-Pour (2000).

- The block economic value (BEV) is considered for each block.
- The set of possible neighborhoods is determined for each block.
- The feasibility of each neighborhood (If the neighborhood elements are located inside the block model or not) is evaluated.
- The economic value of each neighborhood is calculated.
- The maximum value neighborhood is determined.
- The stope economic value is updated.

Ataee-Pour (2000) mentioned that the MVN algorithm failed to determine the true optimal stope layout because it used a heuristic approach with lacks rigorous mathematical proof, however, the MVN algorithm guarantees the optimum value neighborhood for each block. Based on his experience the problem was how to combine these optimum neighborhoods value to create the optimum layout.

Topal et al. (2010) presented a new methodology to find optimum stope layout in case of single as well as variable stope sizes in three-dimensions. The proposed methodology in their work consisted of three basic elements which are block converter, stope boundary optimizer, and stope visualizer.

Block converter has been created to convert a block model with multiple block sizes into a block model with only one size of blocks with new values.

Stope boundary optimizer element uses a range of all the possible stope sizes, ore price per tonne, mining and processing costs per tonne, backfill costs per cubic meter as well as a fixed stope start-up costs as inputs and the optimum stope boundaries and layout for ore-body are the outputs.

The procedure of stope boundary optimizer element is as follow:

Step 1: Optimizer starts from the smallest available stope size on every possible location and it continues to evaluate all the possible stopes and their profits.

Step 2: An envelope is created on every individual stope and the value of each envelope is calculated.

Step 3: Based on the stope profit, stopes are selected.

Step 4: The selected stopes are checked with highest average envelope stope profit from Step 2.

The stope visualizer element is a program to create the three-dimensional view of the final stope layout (Topal et al., 2010).

Their algorithm works based on two assumptions. Firstly, all stopes have a fixed start-up time, and the production and backfill time have a linear relation with the stope volume. Secondly, the calculation of NPV is based on the mining of single stope at a given time.

They have used two different strategies to stope boundary optimization. Firstly, the strategy based on highest profit per stope which shows a better overall profit. Secondly, the strategy based on highest profit per time which demonstrates a better NPV. However, the main problem with his algorithm is failing to analyze all alternative solutions in the procedure (Sandanayake et al., 2015a).

Bai et al. (2013) suggested a new 3D method using flow algorithms to design stopes layout. This model is based on a cylindrical coordinate. They believed that there was not a general-purpose optimization algorithm suited for all underground mining methods because of the difference between geotechnical constraints in different mining methods. As a result, they introduced an optimization algorithm which was suitable only for sublevel stoping (long-hole) method.

Their optimization algorithm includes two main objective functions. The first one is stope optimizer which consists of stope optimizing based on the specified raise location and height. The second one is finding the best raise location and height. In addition, the footwall and hanging wall slope, the stope width and height are played the constraints roles. Also, the maximum distance of a block from the raise and the horizontal width required, for a block at that distance are the control parameters for the cylindrical system of coordinates.

In order to the constraints considering, they have defined the arc in the graph in the cylindrical system and then after finding the overall optimal stope, they have converted the solution to the Cartesian system.

Since their algorithm is based on the cylindrical coordinate system with vertical raise, this algorithm is not acceptable in the case of sub-vertical or sub-horizontal deposits which need inclined raise. Furthermore, this approach is based on the small ore-body with single raise parameters and it isn't useful for larger ore-bodies which need many contiguous stopes. Additionally, in their approach, they have used fixed development costs and operational costs although those are related to the raise location and height (Bai et al., 2013).

Sandanayake et al. (2015a) offered a new 3D heuristic algorithm that maximizes the economic value regarding the physical mining and geotechnical constraints. This algorithm assessed the stope layout problem by considering fixed and variable stope sizes with and without pillars. Also, this group claims that the algorithm is flexible enough for varying underground mining situations.

More specifically, at the first stage, this algorithm transferred the block model to the economic block model. After defining minimum and maximum stope sizes in terms of a number of mining blocks, all possibilities of stopes are created. By getting average, the material density and grade and economic value of each stope are calculated. Then the sets of positive value possibilities are defined. Based on the stope possibilities overlaps, availability of development levels and pillars, the stope possibilities can be limited. The detail of this step is as follows:

Generating sets of non-overlapping stopes, which mentions as equation (3):

$$[c_{xyz_s} \geq l_{xyz_{s'}} \cap c_{xyz_{s'}} \geq l_{xyz_s}; \forall s, s' \in \delta_s] \tag{3}$$

- Adding a constraint if a pillar width and level height (for the 2D situation) defined as equation (4):

$$[\left|c_{x_s} - c_{x_{s'}}\right| \cup \left|c_{y_s} - c_{y_{s'}}\right| \geq p; \forall s, s' \in \delta_{sk}] \tag{4}$$

Where, x_s, y_s, z_s are x, y, and z coordinates of stope s, c_{xyz_s} is x, y, and z coordinates of the origin mining block in stope s, l_{xyz_s} is x, y, z coordinates of the terminal (last) mining block in stope s, δ_s is the sets of stopes with positive economic value, δ_{sk} is the sets of stopes with positive economic value with pillar width apart, and p is the pillar width.

Determining economic value of each non-overlapping stope set, by summation of stopes economic value in each set, and selecting the set with maximum economic value as a solution is another step of the algorithm (Sandanayake et al., 2015a).

Since with infinite sets of stopes, achieving an optimal solution is impossible, they have to define an upper bound on the number of possible solutions. In addition, they reduced the algorithm time by using the parallelization (Sandanayake et al., 2015a).

Sandanayake et al. (2015b) continued their work on finding optimum stope layout, and they prepared an algorithm similar to their previous algorithm with the limitation on a number of the sets of non-overlapping stopes, and they examined the algorithm for an actual ore body model.

To validate the proposed algorithm, they did a comparison with MVN algorithm, which has been implemented in commercially available software. Results indicated that the solution generated by this algorithm achieve to the almost %10 higher economic value than the MVN algorithm. However, the solution time for MVN is less (Sandanayake, 2014).

Villalba Matamoros et al. (2017) worked on the minimization of inherent internal dilution and conventional profit maximization as the main approaches in the optimization of stope layout. The economic, geotechnical and operational and ore-body quality and quantity constraints are subjected in their model.

In their research, they have defined internal dilution, which is the waste or low-grade waste located within the ore, and external dilution, which is the waste low-grade waste located on the border between ore and waste. In addition, they have divided the dilution to two groups of primary dilution and secondary dilution. The primary dilution is inherent in mining method and their stope dimensioning. However, the secondary dilution is additional non-ore material from rock or backfill outside the stope boundaries which can be as a result of blast-induced over break, unstable wall rock fall and backfill fall.

To start their work, some information is used as the input parameters. The minimum and maximum dimension of the stopes have been mentioned as allowable limits to cover the stability of open stopes as well as the efficiency of equipment. A 3D block model of the ore-body is another input information. In addition, the assays of the drillholes and geological model are considered to provide a better knowledge about the quality of the ore-body model.

They describe an objective function which maximizes profit and minimizes dilution as equation (5).

$$\sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{k=1}^{K} xwgRP - \sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{k=1}^{K} xw(M+C) - \sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{k=1}^{K} xwg(1-O)P(R-\zeta(f(g)) \quad (5)$$

Where, *i, j, k* are parameters to show the location of blocks where i= 1, …, I, j=1, …, J, and k = 1, …, K, x is binary variable to show if the block is mined as a part of stope or not, w is the tonnage of blocks, g is the grade of blocks, P is the price of metal by tonnes of metal (\$/oz), M is mining costs per tonne mined (\$/t), C is the processing costs per tonne milled (\$/t), O is binary parameters to clarify if the grade of the block is higher than the cut-off grade or not, ζ is penalty for internal dilution grade recovery to minimize the internal dilution (%), R is recovery of metal, and f is recovery function of blocks with a grade less than cut-off.

The first part of this equation covers the revenue of stopes, the second part includes of mining and processing cost of the stopes, and the last part considers the cost associated with internal dilution which assists to minimize the internal dilution.

This objective function has come with 13 sets of constraints such as constraints to ensure that each block is mined only once, constraints for block precedence, constraints to consider the minimum and maximum of height and width of stopes which should be mined, constraints to define the grade greater than the cut-off.

In the heuristic method presented by Villalba Matamoros et al. (2017), the grade fluctuations in the ore-body can make problem in determining the stope layout correctly. Also, they used uninformed and ultimately costly decisions.

Based on the previous algorithms to determine the optimum stope in an underground mine, there are some important notes which are summarized as follows:

- In all methods, ore block model is adopted as an input. Although, in some of those having only regular and uniform shapes blocks are required, and in some cases, having partial blocks are considered as well.
- Various objective functions are described in the mentioned methods. Maximizing the overall profit or maximizing the NPV are most common objective functions, however, other factors such as minimizing the dilution or maximizing tonnage of ore have been mentioned in some cases.
- Some geotechnical considerations are examined in all algorithms as the constraints to find the optimum slope. However, not all methods are covered all geotechnical constraints. Additionally, in few of previous works, economic constraints, such as mining cost, and operational constraints, such as equipment size, are considered as well.
- Seems dealing with more constraints makes the result closer to the true optimum stope layout.
- Before 2000, few algorithms presented to determine the optimal stope layout. However, some of those did not introduce the 3D models and mathematical solution.
- Simplicity and generality are two characters of some algorithms. Simplicity may cover concepts, assessments and analysis steps in the algorithm. Also, generality is the ability in applying for different mining methods. However, Bai et al. (2013) believed that using one algorithm for all underground mining methods was not a proper decision because of difference in geotechnical constraints in different mining methods.
- All algorithms have covered the minimum sizes of stope, nonetheless, not all of the indicated algorithms have acknowledged the maximum limits of the stope dimensions which from ground control considerations point of view are important.
- Some of the mentioned works are able to calculate only single stope size, but others can evaluate the variable stope sizes as well.
- The shape of the ore body plays an important role in some methods.
- Table 1 is the comparison of all algorithms, which completes the mentioned Table by Ataee-Pour (2000).

At the next section, the new heuristic algorithm which follows the same steps as Sandanayake (2014) research will be introduced. This algorithm can reach to the satisfying result in the short time of running.

3. Proposed Algorithm Methodology

The overall process of the proposed algorithm in this research is generated from five main steps. Fig 1 shows these steps. The process starts by using the economic parameters to create the economic block model. The next step is generating stopes, calculate stopes value and find the positive ones. Then, based on the stopes overlaps, all possibilities of combinations of positive value stopes are found. Also, the value of possible stopes combinations is computed and the optimum stopes combination which is the combination with highest economic value is discovered. Finally, the optimum solution is visualized.

3.1. Generate the Block Economic Model

At the first part, the economic block model is prepared. The blocks information is as the first group of input in the algorithm. The blocks information includes the number, coordinates or indexes, grade, tonnage for each block. The second group of the input is economic parameters which contain the metal price, cost of selling, mining cost, processing costs, and recovery.

Table 1. The comparison of mentioned algorithms

	Algorithm	Model Type	Mining Method	Dim.	Mathematical Formulation	Partial Blocks	True Optimality
1	Dynamic Programming Riddle (1977)	Fixed Blocks	Block-Caving	2D	Yes	No	No
2	Downstream Geostatistical Deraisme et al. (1984)	Cross-Sections	Block-Caving Cut-and-Fill	2D	No	No	No
3	Octree Division Cheimanoff et al. (1989)	Not Applicable	All	3D	No	N/A	No
4	Floating Stope Alford (1996)	Fixed Blocks	All	3D	No	Yes	No
5	Branch and Bound Ovanic et al. (1995)	(Ir)regular Blocks	All	1D	Yes	Yes	Yes
6	MVN Ataee-Pour (2000)	Fixed Blocks	All	3D	No	No	No
7	Methodology by Topal et al. (2010)	Not Applicable	All	3D	No	No	No
8	Network Flow Method Bai et al. (2013)	Cylindrical Coordinate	Sublevel Stoping	3D	Yes	No	No
9	Methodology by Sandanayake (2014)	(Ir)regular Blocks	All	3D	No	No	No
10	Methodology by Villalba Matamoros et al. (2017)	Not Applicable	All	3D	No	No	No

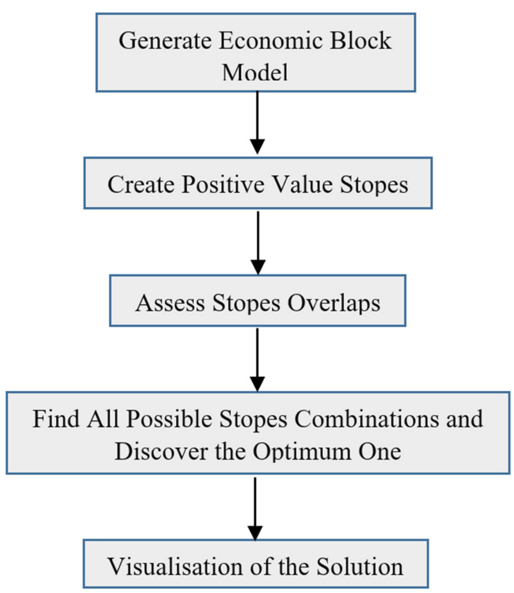

Fig 1. Overall process of the algorithm

To calculate the economic value for each block, the cut-off grade, which is the lowest sufficient grade of the material to send it to the processing, is required. In fact, if the grade of the block is more than the cut-off grade, the economic value of the block is computed by equation (6). However, if the grade of the block is less than the cut-off grade, the equation (7) should be applied and that block is considered as a waste.

$$v = \left[(p - c_s) \times g \times r - (c_m + c_p) \right] \times t \tag{6}$$

$$v = -(c_m \times t) \tag{7}$$

Where v is the block economic value ($), p is the metal price ($/tonne or $/oz), c_s is the cost of selling ($/tonne), g is the block average grade (oz/tonne or %), r is recovery, c_m is the cost of mining ($/tonne), c_p is the cost of processing ($/tonne), and t is the tonnage of the block (tonne).

3.2. Create Positive Values Stopes

At the first step, based on geotechnical and mining constraints, the dimensions of the stopes should be defined. The dimensions of the stopes are based on the number of the blocks at three directions (X, Y, Z axes) which called Lx, Ly, and Lz. Then, the stope with these dimensions is floated along axes to find all stope possibilities. Fig 2 indicates an example of a 2D economic block model with 6 blocks along X-axis and 4 blocks along Y-axis. Also, it shows the starting point for stope floating. In this example, +2 is considered as the value of each block.

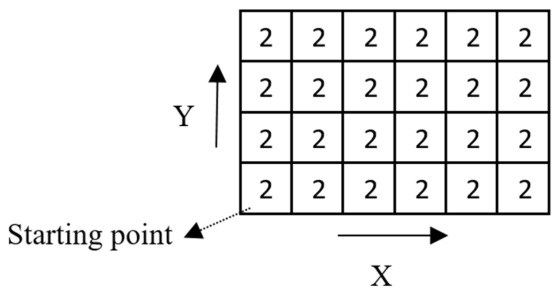

Fig 2. An economic block model (6×4)

Fig 3 illustrates how a 3×3 (Lx=3, Ly=3) stope can float along the axes to create all stope possibilities, which in this case 8 possibilities have been created. Then, the value of each stope should be calculated which is the summation of all blocks value in each stope. For instance, in the current example, the value of 9 blocks are summed to have the value of each stope which equals to +18. Finally, stopes with the positive value are the output of this step.

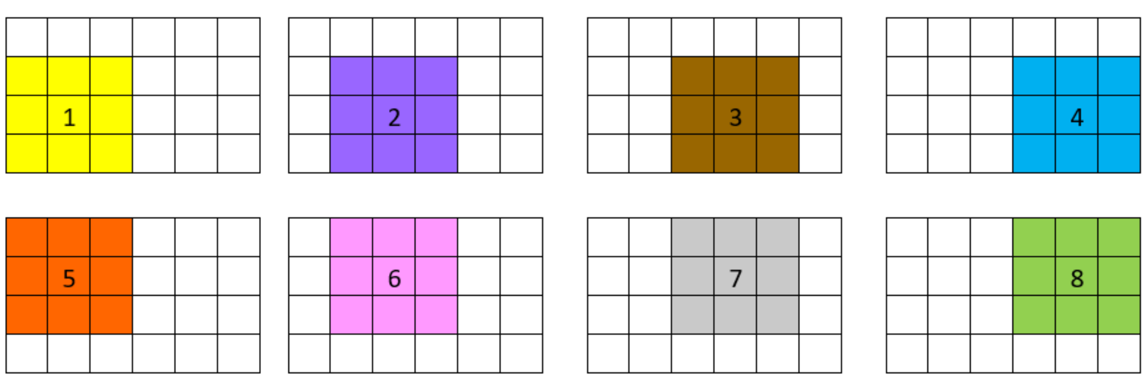

Fig 3. All possible positive stopes

3.3. Assess Stopes Overlaps

This step is about finding possible combinations of stopes with positive economic value. The main consideration in this step is discovering the overlaps between these stopes. In reality, not all stope can combine together because of exciting overlaps between those stopes.

To do this step, an all zero elements matrix with same dimensions of i and j, and equal to a number of positive stopes is created and by looping over all the elements, overlaps can be found. In fact, if two elements (two positive stopes) have one or more common blocks, those are accounted as the stopes with overlap. In the presented algorithm, if two stopes have overlap, element zero is changed to one in the overlap matrix. While, if two stopes do not have any overlaps, element zero is kept in overlaps matrix. As a result, the overlap matrix, a matrix with elements zero and one, is created.

For example, in Fig 4, it is not possible to have stope number 1 and number 7 or number 6 and number 8 at the same time.

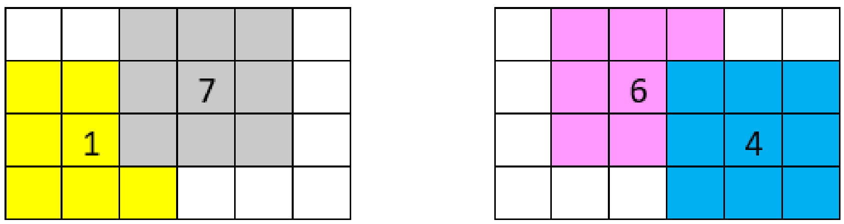

Fig 4. Examples of stope possibilities overlap

3.4. Find All Possible Stopes Combinations and Discover the Optimum One

At this step, the presented algorithm creates the possible stopes combinations. In facts, these combinations can be generated by eliminating the stopes overlaps in each possible combination. For instance, for mentioned case, the result of this step is as Fig 5 with 4 acceptable combinations. After discovering all stope combination, it is time to calculate the economic value of each combination which is a summation of all stopes value in each combination set.

At this step, the values of all combination should be compared and the best one should be discovered. The best combination is the combination with highest economic value. The problem can be formulated as a knapsack problem with conflict graph. In this analogy, the positive stopes are items that can be picked to put in a knapsack, the weights are all equal to one and the positive stope values are the utilities.

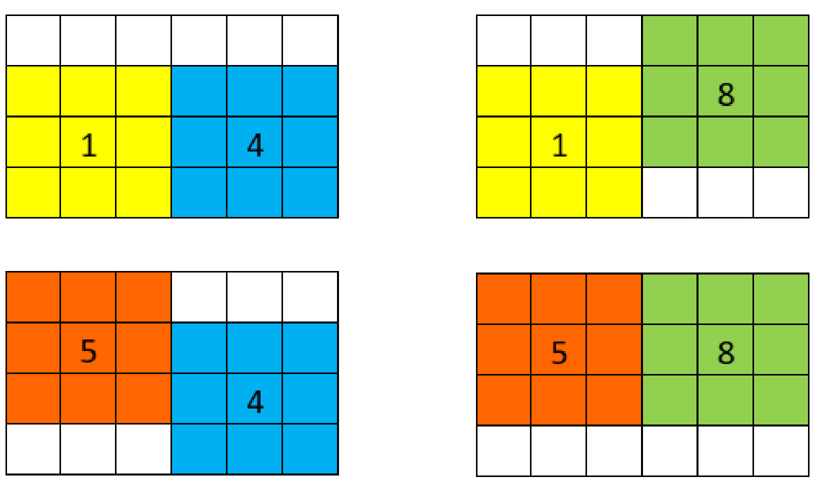

Fig 5. Possible stopes combination sets

Pferschy et al. (2009) used the standard 0-1 knapsack problem and added the weight and the incompatibilities for certain pairs of items as the constraints. They defined that from each conflicting pair the highest value item can be packed into the knapsack. Also, to model the conflicts between the items, they used conflict graph. The graph is represented by a $n \times n$ matrix where the value of *(i,j)* is equal to 1 if the two items cannot be packed together.

Equations (8) presents the formulation of the objective function and equations (9) to (11) indicate the constraints.

Objective function

$$\max \sum_{j=1}^{n} p_j x_j \tag{8}$$

Where n is a number of items, i and j are indicators of the items, p_j is the utility of each item and x_j is the decision variable indicating whether item j is picked in the knapsack. To employ Knapsack problem with conflict graph and find the optimum positive stopes combination, n, i and j, p_j and x_j refer the number of the positive stopes, positive stopes indicators, the value of the positive stopes and the decision variable to show whether stope j is in the optimum combination, respectively. This objective function uses one set of the variable for making a decision about considering each positive stopes in the optimum stopes combination with the highest value or not. In fact, this objective function is to maximize the value of positive stopes combination.

Constraints

$$\sum_{j=1}^{n} w_j x_j \leq c \tag{9}$$

$$x_i + x_j \leq 1 \forall (i,j) \in E \tag{10}$$

$$x_j \in \{0,1\} \; j = 1,...,\mathrm{n}. \tag{11}$$

Equation (9) indicates one of knapsack constraint, where, c is Knapsack capacity and w_j is the weight of each item. In our case, the capacity of the knapsack is equal to the total number of positive stopes and the weights are equal to one. Equation (10) models the conflict and incompatibility of the positive stopes where E is the set of positive stope indices with overlap. In fact, not two positive stope possibilities with overlap can be in the solution together, however, one of those can be included in the solution. Equation (11) defines the decision variables as the binary variables.

3.5. Visualization of the Solution

The output of this step is the plot of the best stopes combination possibilities which are the highest value combination. Fig 6 shows algorithm process with detail.

4. Implementation of the Algorithm

The algorithm has been tested by applying in the real block model, McLaughlin gold mine, located in CA, USA. This block model contains 68 elevations. To decrease the number of blocks and simplify the problem, only three elevations (22 to 24) have been used. Table 2 indicates the information of the blocks in these elevations. Fig 7 shows the situation of the blocks in these elevations.

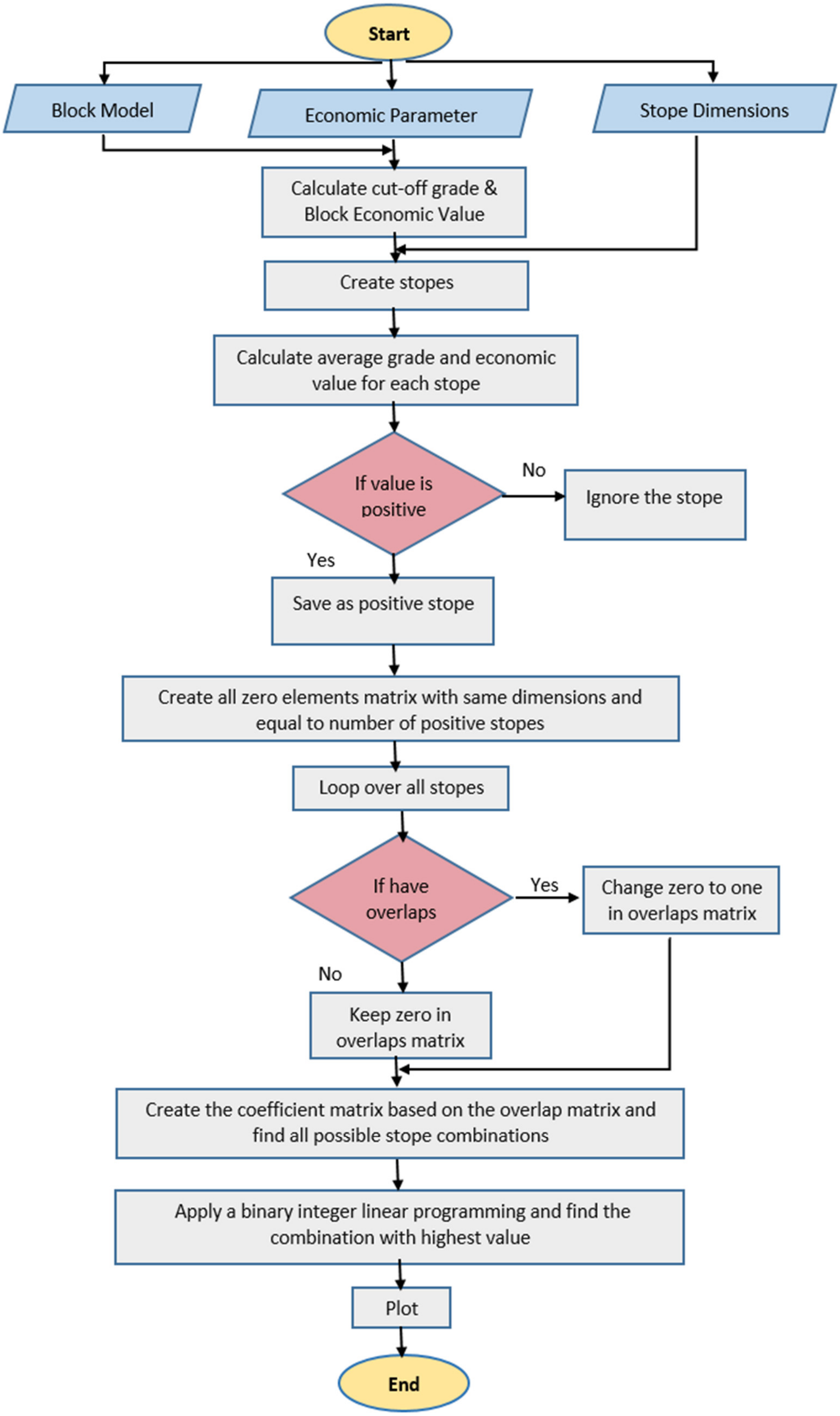

Fig 6: Algorithm to find the optimum stope layout

Table 2. Block model information

Number of blocks	15,577
Blocks size (ft)	25×25×20
Blocks tonnage(tonn)	From 177.08 to 1041.67
Blocks grade (oz/tonn)	From 0 to 1.546
X Coordinate (X index)	6-63
Y Coordinate (Y index)	1-199
Z Coordinate (Z index)	22-24

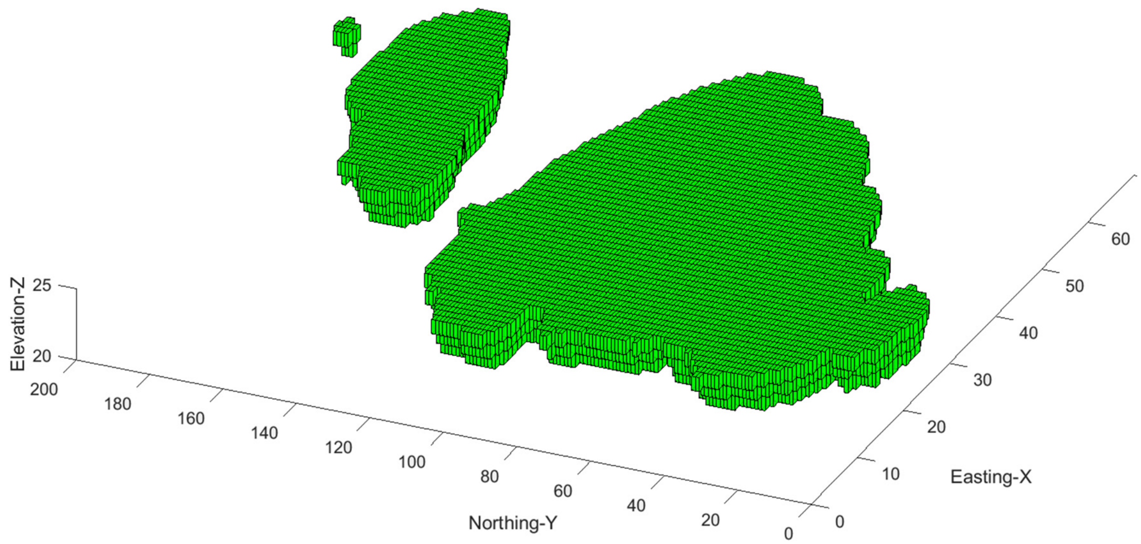

Fig 7. The block model

4.1. Generate the Block Economic Model

To calculate the block economic value, the economic parameters are required, which are listed in Table 3.

Table 3. Economic parameters

Metal price (Au)	$900/oz
Cost of mining	$1.32/tonn
Cost of processing	$19/tonn
Recovery	90%

To determine waste or ore blocks, calculating the cut-off grade is the first step. Then, if the block has a grade more than cut-off grade, equations (6), and if the block grade is less than the cut-off grade, equation (7) is used to calculate an economic value for each block. These calculated values are between $-1,375 and $+1,283,275.

4.2. Create Positive Values Stopes

Based on the rock mechanics considerations, stope dimensions, 3×3×3 is chosen for this study. However, there is the possibility of changing dimensions and scanning the impacts of that.

Creating stopes and separating the positive ones are the next steps. In this block model, 4,818 stopes are generated which 3,212 of those have positive economic value.

It is notable that not all blocks in the initial block model have data. As a result, there are not 27 blocks available to create some stopes. To overcome this matter, the presented algorithm defines stope with more than 20 blocks.

4.3. Assess Stopes Overlaps

In this step, the 3212×3212 overlap matrix is created. This matrix contains 0 value for positive stopes which do not have overlap and 1 value for positive stopes which have overlap. By using computer with processor: Intel(R) Core(TM) i5-4460 CPU @ 3.20GHz and RAM: 6:00 GB, the solution time for this part is 00:04:59.

4.4. Find All Possible Stopes Combinations and Discover the Optimum One

Based on the equations (8) to (11), to employ the presented algorithm to find the optimum positive stopes combination, n, p_j and c should be determined. In this case study, n and c, which is equal to a total number of positive stopes, are 3212 and p_j are the value of those positive stopes.

By running the algorithm, 72,342 positive stopes combinations are created and with zero percent gap, the optimum combination with 368 positive stopes is discovered. The value of this combination is $321,1 M, which is the maximum achievable value of extracting these three levels of McLaughlin mine. Also, the solution time for this part is 00:00:06.

4.5. Visualization of the Solution

Fig 8 indicates the stopes in the final result of the algorithm. The selected stopes in the best stopes combination are demonstrated with the different colors. Also, the blocks in each stope are shown. Some stopes contain less than 27 blocks because as it mentioned before, there is no data available for every block at the initial block model.

5. Summary and Conclusion

This paper presented a method to finding the optimum stopes layout with highest economic value. The presented heuristic algorithm in this method was applied to the gold deposit. It reached to an appropriate result with a minimum percentage of the gap with exact solution in the short time. In fact, the total solution time from beginning to plotting the optimum solution is 00:07:20. Table 4 demonstrates the summary of the solution.

Table 4. Summary of the solution

Number of blocks in the solution	368
The value of the solution	$321,1 M
The solution time	00:07:20

In future, the presented algorithm will be improved in some areas such as production scheduling. Also, I have a plan on upgrading this algorithm by considering more than one mineral type, for example, gold and copper.

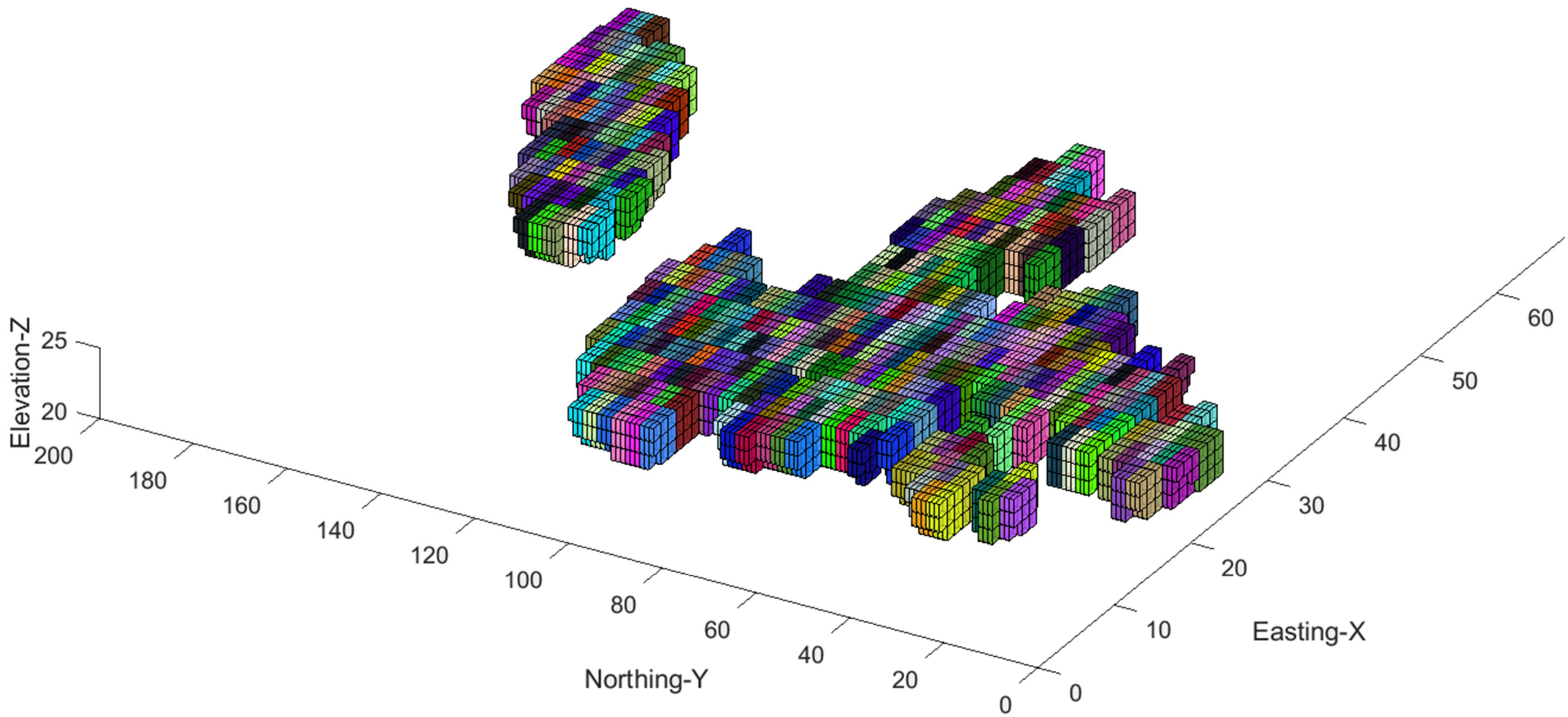

Fig 8. The optimum solution (stopes)

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A Greedy Algorithm for Stope Boundaries Optimization

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ABSTRACT

One of the main steps after selecting underground mining method is determining stope boundaries. Obviously, regarding its impacts on mining economy, it should be an optimal plan. However, due to the problem complexities, a comprehensive algorithm has not been reported yet for it. Most of the presented algorithms are heuristic for which the true optimality is not guaranteed. Also, other algorithms whose solutions are seemed to be optimal, either fail to run on 3D problems or their applications are limited to a specific method. This paper introduces a new greedy algorithm. Although this proposed algorithm may fail to provide a globally optimum solution, it is a polynomial time algorithm. After algorithm description, it has been compared to MVN algorithm. Results show that this algorithm may find a higher value solution compared to its alternatives.

1. Introduction

As open pit mines deepen their stripping ratio and consequently their mining costs are increased. In these situations, extracting the rest of deposit by one of the underground mining methods may be more economically. Also, for some of the deposits in which overburdens are large enough, the underground mining methods are our only options. Given one of these underground methods as the suitable method for extracting the ore deposit, it is necessary to determine the optimal workable layout. Clearly, this layout should be as optimal as possible. However, after four decades from the presentation of the first algorithm for optimizing underground mining limit, the growth rate of these algorithms had been slow within this passed period. The majority of presented algorithms are heuristic, as well as, their solutions are suboptimal. Moreover, the presented rigorous algorithms either are not 3D or they have many simplifications.

Open pit and underground optimization algorithms are usually implemented on 2D or 3D economic block models. Indeed, a large cube covers the whole of the ore deposit and part of waste rocks. Afterwards, using the parallel vertical and horizontal planes, the large cube is divided into smaller cubes which are usually regular. Each of these smaller cubes is called a block and owns a specific position and also dimensions. In the next step, using one of the estimation methods, block grade is estimated. By knowing the mining cost, commodity price, and recovery, block economic value (BEV) is calculated.

The main purpose of optimizing underground mining limit is a determination of an appropriate plan for choosing a combination of blocks in the economic models that maximizes the overall profit, subject to some constraints.

Some researchers have been looking at optimization of stope boundaries since four decades ago such as; Riddle (1977), Ovanic and Young (1995, 1999), Alford (1995), Ataee-pour (1997), Jalali and et al (2004), Topal and Sens (2010), Bai and et al (2013, 2014). However, most of the presented algorithms are heuristic, as well as, their solutions are suboptimal. Moreover, the presented rigorous algorithms, either is not 3D or they have many simplifications. Although these heuristic algorithms usually fail to provide an optimal solution they are useful techniques to solve our large-scale problem at a reasonable time.

This paper proposes a new greedy algorithm for stope boundaries optimization. It is a heuristic algorithm and may not find out the global optimum solution. However, it has a great potential for solving such large-sized problem.

2. Proposed Algorithm

Indices, parameters, sets, and variables which are used in this algorithm are defined as below:

Index

t	stage number

Parameters

P	economic block model
$p_{i,j,k}$	value obtained from extracting block $B_{i,j,k}$
I	number of P blocks along i axis
J	number of P blocks along j axis
K	number of P blocks along k axis
d_i	minimum stope size in terms of block along i axis
d_j	minimum stope size in terms of block along j axis
d_k	minimum stope size in terms of block along k axis
$B_{m,n,o}$	origin block of a probable stope
$B_{\tilde{m},\tilde{n},\tilde{o}}$	origin block of a definitive stope

Sets

M	feasible locations of origin blocks along i axis
N	feasible locations of origin blocks along j axis
O	feasible locations of origin blocks along k axis
$S_{m,n,o}$	blocks which are located in a probable stope
$S_{\tilde{m},\tilde{n},\tilde{o}}$	blocks which are located in a definitive stope

Variables

$\varphi^t_{m,n,o}$	value added to overall stope value from extracting a probable stope at the t^{th} stage
$\varphi^t_{\tilde{m},\tilde{n},\tilde{o}}$	value added to overall stope value from extracting a definitive stope at the t^{th} stage
Λ^t	optimal stope boundaries which is the union of all definitive stopes at the t^{th} stage

λ^t	overall stope value at the t^{th} stage
Ω^t	non-investigated stopes set
Θ^t	pre-investigated stopes set

2.1. Probable and Definitive Stopes

A probable stope is a subset of P and denoted by $S_{m,n,o}$. This subset creates a cube that its dimensions along i, j and k axis are fixed and they are pre-known parameters. These dimensions are also named as minimum stope sizes. Each cube is determined by an origin block ($B_{m,n,o}$, yellow blocks in Fig. 1).

Since $S_{m,n,o}$ satisfies minimum stope size constraints, it has a potential to be chosen as part of the final layout. However, based on the problem's objective function (it can be maximization of profit, NPV, etc) the algorithm might reject it. Therefore, it is called a probable stope. When a probable stope is decieded to be included in the optimal solution, its name changes to definitive stope. The relationship between a probable stope and its blocks is presented in Eq (1).

$$S_{m,n,o} = \{B_{i,j,k} \mid i \in \{m,\ldots,m+d_i-1\}, j \in \{n,\ldots,n+d_j-1\}, k \in \{o,\ldots,o+d_k-1\}\} \quad (1)$$

Also, feasible locations of origin blocks along i, j and k axis are defined by M, N and O sets (Eqs. (2) and (4)).

$$M = \{1,2,\ldots,I-d_i+1\} \quad (2)$$

$$N = \{1,2,\ldots,J-d_j+1\} \quad (3)$$

$$O = \{1,2,\ldots,K-d_k+1\} \quad (4)$$

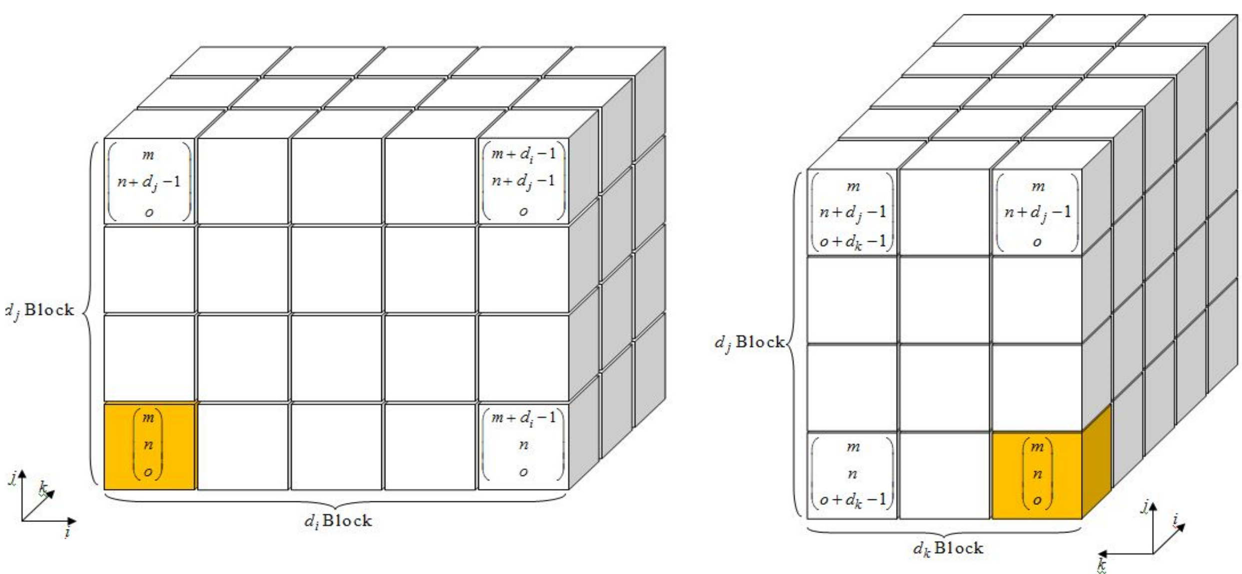

Fig. 1. A 3D view of a probable stope

2.2. Greedy Algorithm

Based on the type of objective function, e.g. maximization of profit, a greedy algorithm at each stage selects the best solution without considering its previous and future decisions. Obviously, these approaches may lead to a local and near-optimal solution. Although they do not guarantee a global solution, they are very fast and useful algorithms to solve any large-scale problem at a polynomial time.

In this paper, it is tried to propose a new greedy algorithm for optimization of stope boundaries considering minimum stope sizes. The main core of this algorithm is to find the most valuable probable stope between non-investigated stopes set by Eq. (5). This stope is called definitive stope and it is added to the optimal stope boundaries set (Λ^t) if its value is positive (Eq. (6)). Since the algorithm checks any stopes only once, any definitive stope is removed from non-investigated stope sets (Ω^t), Eq. (7), and is added to pre-investigated stope sets (Θ^t), Eq. (8).

$$\varphi^t_{\tilde{m},\tilde{n},\tilde{o}} = \max\{\varphi^t_{m,n,o} \mid B_{m,n,o} \in \Omega^{t-1}\} \tag{5}$$

Where:

$$\varphi^t_{m,n,o} = \sum_{(i,j,k)\in(S_{m,n,o}-\Lambda^{t-1})} p_{i,j,k}$$

$$\Lambda^t = \Lambda^{t-1} \bigcup S_{\tilde{m},\tilde{n},\tilde{o}} \tag{6}$$

$$\Omega^t = \Omega^{t-1} - B_{\tilde{m},\tilde{n},\tilde{o}} \tag{7}$$

$$\Theta^t = \Theta^{t-1} \bigcup B_{\tilde{m},\tilde{n},\tilde{o}} \tag{8}$$

At the beginning of algorithm, pre-investigated stope set (Θ^0) and also the stope boundaries set (Λ^0) are empty, because the algorithm has not found any definitive stope yet. However, the initial non-investigate stope set (Ω^0) consists of all feasible origin blocks (Eq. (9)).

$$\Omega^0 = \{B_{i,j,k} \mid i \in M, j \in N, k \in O\} \tag{9}$$

Also, the overal stope value at each stage (λ^t) is determined by Eq. (10).

$$\lambda^t = \lambda^{t-1} + \varphi^t_{\tilde{m},\tilde{n},\tilde{o}} \tag{10}$$

The pseudo code of this algorithm has been illustrated in Fig. 2.

3. Numerical Example

Let us suppose that there is a section of the economic block model with six rows and ten columns (Fig. 3), and minimum stope sizes along i and j axis to be equal to three and one blocks, respectively. Based on the following calculations the greedy algorithm determines a layout with a value of 63 (Fig. 4). However, the MVN algorithm determines a layout with a value of 59 when its search direction is from the right side to left side (Fig. 5).

algorithm *greedy algorithm for stope boundaries optimization*;

begin

1) $t := 1$;

2) $\Omega^0 := \{B_{i,j,k} \mid i \in M, j \in N, k \in O\}$;

3) $\Theta^0 := \varnothing$;

4) $\Lambda^0 := \varnothing$;

5) $\lambda^0 := 0$;

6) find a stope with the maximum value among the non-investigated stopes:

$\varphi^t_{\tilde{m},\tilde{n},\tilde{o}} = \max\{\varphi^t_{m,n,o} \mid B_{m,n,o} \in \Omega^{t-1}\}$ and $B_{\tilde{m},\tilde{n},\tilde{o}} \in \Omega^{t-1}$

7) remove this stope from the non-investigated stopes set (Ω^t) and add it to pre-investigated stopes set (Θ^t):

$\Omega^t = \Omega^{t-1} - B_{\tilde{m},\tilde{n},\tilde{o}}$

$\Theta^t = \Theta^{t-1} \bigcup B_{\tilde{m},\tilde{n},\tilde{o}}$

While $\varphi^t_{\tilde{m},\tilde{n},\tilde{o}}$ is positive **do**

begin

a) update stope boundaries (Λ^t): $\Lambda^t = \Lambda^{t-1} \bigcup S_{\tilde{m},\tilde{n},\tilde{o}}$

b) update overall stope value (λ^t): $\lambda^t = \lambda^{t-1} + \varphi^t_{\tilde{m},\tilde{n},\tilde{o}}$

c) $t := t+1$;

d) go to step 6

end;

end;

Fig.2. Pseudo code of the greedy algorithm

i \ j	1	2	3	4	5	6	7	8	9	10	11	12
1	2	1	-1	0	3	2	-2	4	1	2	-2	-1
2	5	-1	-1	2	3	-2	1	0	1	3	-1	-1
3	3	0	4	1	-2	-1	0	-1	2	1	-1	2
4	-1	0	-2	1	2	0	4	-1	1	2	2	-1
5	6	-1	-3	1	0	-3	5	3	1	-4	2	0

Fig. 3. The economic block model example

$$\boldsymbol{t=1:}(\tilde{m},\tilde{n})=(5,7),\varphi^{1}_{(5,7)}=9,\Theta^{1}=\{B_{5,7}\},\Lambda^{1}=\{S_{5,7}\},\lambda^{1}=9$$

$$\boldsymbol{t=2:}(\tilde{m},\tilde{n})=(1,8),\varphi^{2}_{(1,8)}=7,\Theta^{2}=\{B_{5,7},B_{1,8}\},\Lambda^{2}=\{S_{5,7},S_{1,8}\},\lambda^{2}=16$$

$$\boldsymbol{t=3:}(\tilde{m},\tilde{n})=(3,1),\Phi^{3}_{(3,1)}=7,\Theta^{3}=\{B_{5,7},B_{1,8},B_{3,1}\},\Lambda^{3}=\{S_{5,7},S_{1,8},S_{3,1}\},\lambda^{3}=23$$

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.

$$\begin{aligned}&\boldsymbol{t=17:}(\tilde{m},\tilde{n})=(5,2),\Phi^{17}_{(5,2)}=1,\\&\quad\Theta^{17}=\{B_{5,7},B_{1,8},B_{3,1},B_{4,5},B_{1,4},B_{4,9},B_{2,3},B_{2,8},B_{2,1},B_{1,1},B_{3,9},B_{5,1},B_{3,10},B_{2,7},B_{3,2},\\&\qquad B_{4,4},B_{5,2}\},\\&\quad\Lambda^{17}=\{S_{5,7},S_{1,8},S_{3,1},S_{4,5},S_{1,4},S_{4,9},S_{2,3},S_{2,8},S_{2,1},S_{1,1},S_{3,9},S_{5,1},S_{3,10},S_{2,7},S_{3,2},\\&\qquad S_{4,4},S_{5,2}\},\\&\quad\lambda^{17}=63\end{aligned}$$

$$\boldsymbol{t=18:}(\tilde{m},\tilde{n})=(1,2),\Phi^{18}_{(1,2)}=0,\text{it is not a positive number}\rightarrow\text{End}$$

i \ j	1	2	3	4	5	6	7	8	9	10	11	12
1	2	1	-1	0	3	2	-2	4	1	2	-2	-1
2	5	-1	-1	2	3	-2	1	0	1	3	-1	-1
3	3	0	4	1	-2	-1	0	-1	2	1	-1	2
4	-1	0	-2	1	2	0	4	-1	1	2	2	-1
5	6	-1	-3	1	0	-3	5	3	1	-4	2	0

Fig. 4. The greedy algorithm output with value of 63

i \ j	1	2	3	4	5	6	7	8	9	10	11	12
1	2	1	-1	0	3	2	-2	4	1	2	-2	-1
2	5	-1	-1	2	3	-2	1	0	1	3	-1	-1
3	3	0	4	1	-2	-1	0	-1	2	1	-1	2
4	-1	0	-2	1	2	0	4	-1	1	2	2	-1
5	6	-1	-3	1	0	-3	5	3	1	-4	2	0

Fig. 5. MVN output with value of 59

4. Conclusion

Undoubtedly, underground mining limit optimization is one of the main mining problems which play an important role in the industrial mining economy. However, after four decades since the first algorithm has been presented for this problem, there is no complete algorithm yet. Most of them are heuristic and their solutions are not guaranteed. Also, due to many simplifications in designing rigorous algorithms, they are not appropriate to solve real case problems. In this research, a new greedy algorithm was introduced. Although it may provide a locally optimum solution, it is able to find the solution at a reasonable time. Actually, less processing time for running this algorithm is very important due to our hardware limitations.

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Investigation on the Use of Chemical Dust Suppressants on Ash Emissions Due to Fort McMurray Wildfire

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ABSTRACT

A large-scale wildfire had broken out at Fort McMurray in Alberta, Canada during May 2016. Many oil sands mining activities were affected due to the wildfire and the associated ash emissions. In particular, ash emission generated from the fire outbreak is a huge problem during the post-fire cleanup. These emissions pose a severe health hazard to workers, environment and global climate. The ashes emitted into the atmosphere are caused by either human activities or climate conditions. The objective of this research is to assess the effect of three different ash dust suppressants, namely water, #1 surfactants, and #2 polymers at various volumetric concentrations on ashes samples to prevent propagation of fine solid emissions into the atmosphere. It is found that both #1 surfactants solution and #2 polymers solution are effective in retaining fugitive ash dust generated from the ashes. Volumetric concentration efficiency of 0.05% of #1 surfactant and 5% of #2 polymers in 500 ml of water have been proven to provide ash dust retention efficiency greater than 99% after the spraying of these suppressants. It is also found that both #1 surfactants solution and #2 polymers solution maintain an ash dust retention efficiency higher than that of the use of only water. This confirms the merit of using chemical dust suppressants on fugitive ash dust for a longer period, which is proven by the 72-hour data from this experiment. This study gives a general view of how effective chemical suppressants on fugitive ash emissions work.

1. Introduction

On May 1st, 2016, a large-scale wildfire gutted Fort McMurray, Alberta, Canada. Many oil sands mining activities were affected due to the wildfire and the associated ash emission. Due to the wildfire, some of the biggest oil sands companies in Fort McMurray such as Royal Dutch Shell and Suncor Energy shut down their oil production, at 255,000 and 350,000 barrels per day respectively [1]. Syncrude Canada Ltd scaled down its normal production capacity level of 350,000 barrels per day [1]. This generated an estimated loss of about 1.1 million barrels of oil production per day, constituting a 30% reduction in the Canadian daily oil production, crippling the economy [2]. This loss in production by the companies translated into 0.33 % of the Alberta GDP in 2016 constituting a loss of $985 million and 0.06 % of the entire Canadian economy [3]. In 2017, it is estimated that the rebuilding and reclamation of the affected areas in Fort McMurray will add $ 1.3 billion in GDP to the Alberta's economy [3].

This paper, in its entirety, was presented in SME Annual Meeting (SME 2017), Denver, USA, Feb 19-21, Preprint 17-077.

A population of over 90,000 people was evacuated form the location and its surroundings for health and safety reasons [4]. The fire destroyed about 2,400 structures and over 500,000 hectares of forest vegetation in Fort McMurray, leaving an estimated 232,000 tonne of post-fire ashes [5,6].

As the fire got under control, one serious problem presented during the cleaning and reclaiming of the post-fire sites is the emission of the dust from the ashes into the environment, since wood ashes were produced as the byproduct of burnt forest vegetation and structures. According to Alberta Health Services, the produced ashes contain arsenic and other heavy metals, making the surrounding homes and environment unsafe for living. The release of the heavy metals into the environment can cause major health issues such as hematological disorder, chronic lungs disease, diabetes mellitus, low birth weight, cardiovascular diseases, and lungs and kidney problems [7]. The produced ashes were tested and shown high PH value, which can lead to skin burns and irritations [8–10].

Canada as one of the countries that signed the international treaty of conference of the parties (COP) at the 21st United Nations Climate Change Conference held in France has an obligation to combat climate change. The country under this treaty is currently committed to reduce the emissions of short-lived climate pollutants (e.g., fugitive ash dust) into the atmosphere, which is a significant contributor to global warming, by 30% on 2030 [11]. Therefore, it is of great significance to control the fugitive ash dust within its allowable borders in Fort McMurray [11,12].

According to the 2012 final report of the Canadian-wide standards for particulate matter and ozone's, the average daily value for the Alberta ambient air quality guideline of PM 2.5 µm per location is 30 µg/m3 per day [13]. However, according to Alberta Health Services, Fort McMurray and its surrounding cities exceeded the concentration limit reported by Environment Canada over 20 times due to the fire ashes [8,9]. Hence, post-fires ashes must be controlled effectively to ensure a safe living and working environment in Fort McMurray.

Water over the years has been used as the traditional method for controlling the emission of normal fugitive dust (e.g., road dust and coal dust) into the atmosphere. However, water requires consistent re-application due to a high evaporation rate; this is not favored as more water needs to be consume and the overall efficiency will be reduced [14–16]. Water over the years has been used as the preliminary method for controlling the emission of fugitive ash dust into the atmosphere. However, it has some limitations that make it less efficient. The molecules structure within water is separated from each other, which reduces the adhesive bond and creates a high surface tension. The high surface tension increases the evaporation rate of the water, which in terms reduces the fugitive ash dust retention efficiency [14–18]

Chemical suppressants on the other hand can improve the efficiency of fugitive ash dust retention and reduce the need of re-application [14,15]. The addition of chemical suppressants to water will help improve molecule bonding by increasing the cohesive force. This will decrease the surface tension of the solution and the evaporation rate [14–16].

Post-fire ash is different from normal fugitive dust since it contains more toxic and hazardous compounds (e.g., arsenic, benzene) and a high PH value, and may also have heavy carbon contents [7,8]. At present, the use of chemical dust suppression agent on post-fire ash dust is rarely investigated.

Hence, the objective of the study is to assess the effect of three different ash dust suppressants to control the emission of fugitive ash dust generated from post-fire ashes due to the recent Fort McMurray wildfire.

2. Experimental Detail

2.1. Material

A sample of ashes from the Fort McMurray fire outbreak was received on May 9th, 2016 from a local company. A total of 20 kg of the ash samples were received in a sealed bag. As shown in Fig 1, the ash samples were composed of coarse and fine solid particles, including large wood chunks, coal, and fine ashes.

Fig 1. A photo of fire Ash from Fort McMurray

2.2. Ash Dust Suppressants

Two chemical suppressants provided by a local company and water were tested as the control means for controlling the emission of fugitive ash dust into the atmosphere. Suppressants such as water, #1 surfactants, and #2 polymers were examined. Fig 2 shows the dust suppressant agents considered for this research**.**

Fig 2 (1) presents the tap water used in the research. The used water meets the acceptable concentration limit of 80 µg/L, as the running annual average of water for all chemicals, physical and radiological parameters set by Health Canada [19]. This makes the tap water free from impurities and safe for experimental purposes.

Fig 2 (2) shows the #1 Surfactants solution. The #1 surfactant is a non-flammable yellowish liquid with potential of hydrogen (PH) value ranging from 8-9; the boiling point is 100 ^{o}C and the specific gravity is 1.0. This chemical has the capability of binding widely space molecules of water together to form a stronger bond by decreasing surface tension [14,16,20].

Fig 2 (3) shows the #2 Polymers solution. The #2 polymers solution is non-flammable white liquid with a PH value ranging from 8-9, and has a boiling point of 100 ^{o}C and a specific gravity of 1.03. This suppressant can keep the separated water molecules closer to form an adhesive bond and reduces the evaporation rate of the solution [14,16,20].

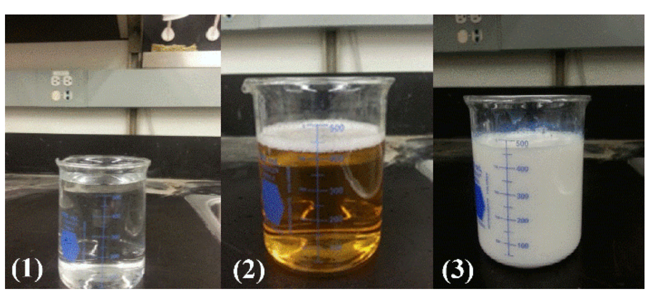

Fig 2. Dust suppressant agents used in the study; (1) Water, (2) #1 Surfactants solution, and (3) #2 Polymers solution

2.3. Test Methods

The ash sample was dried in an oven at a controlled hot climate of 60 °C for 72 hours. These parameters were selected as the optimum temperature and time for the drying out all the moisture content present within the ash sample based on the material size of the ash sample. At a temperature of 60 °C the sample will be fully dry after 72 hours. Through this process, all the moisture content present in the sample was taken out. Because the samples tested were composed of chunks of burnt woods, coal, and fine ash particles, screening process is used for separating the coarse particles from the fine particles by performing a sieve analysis test with mesh opening ranging from 3.35 mm to 750 µm. This mesh size was chosen to obtain ashes with smaller particle sizes, which are the main source of fugitive ash dust flying that stays in the atmosphere. Climate conditions such as wind velocity, temperature, and humidity play a significant impact on the amount of ash particles emitted into the atmosphere and the efficiency of a suppression agent in controlling the ash dust emission [15,18,21,22]. According to the weather statistics of Fort McMurray from Environment Canada, the maximum average wind speed and temperature at Fort McMurray for the past five years in the second quarter (April- June) are 55 km/h and 33 °C respectively [23].

These parameters were selected as the base conditions for this experiment because they had been shown over the last five years to be the highest temperature and wind condition, which is considered as the extreme weather condition for the location of the fire outbreak. Stipulated time intervals of 3 hours, 6 hours, 24 hours, 48 hours and 72 hours were considered to be the time bases for the experiment. Three series of ash samples are tested for each suppressant per stipulated period, with the average taken as the reported value of the series. Fig 3 is a schematic diagram showing the principles behind the experimental procedure. Likewise, Fig 4 shows the actual experimental set-up.

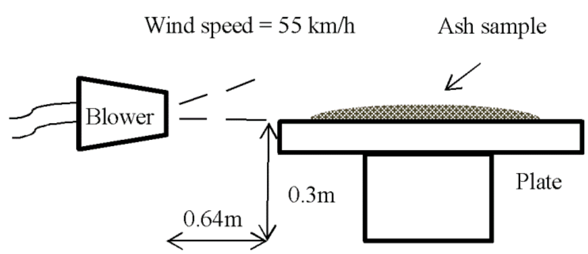

Fig 3. Schematic representation of experimental procedure

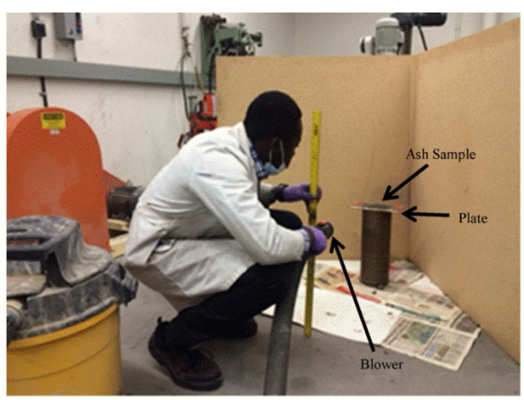

Fig 4. Photo showing the experimental set up

In proving the efficiency of each tested suppression agent in controlling the fugitive ash dust emission, a control baseline of no suppressant applied to the ash sample is tested. An ash sample weighting 15 g is placed in an oven at a temperature of 33 °C per stipulated duration. The sample is then with a wind speed of 55 km/h. After blowing this wind weighed on a scale before being blown at to the sample, no ash sample remained on the plate. This base process showed 0% ash retention efficiency on the plate after the wind effect, which prompt the testing of ash dust suppressant to reduce fugitive ash dust.

Water is the first suppression agent tested on the ash sample for the control of the emission of fine particles in the atmosphere. Water as an ash suppressant needs no dilution with any surfactant at the initial stage of its usage since it is regarded on its own as an ash suppression agent. 15 g of ash sample is measured on a laboratory scale. 30 ml of water is applied to the sample using a sprinkler. The sample is then placed in a controlled hot temperate oven of 33 ^oC for 3 hours. After the required duration is reached, the sample is weighed on a scale to know its weight before being blown with wind speed of 55 km/h to the sample (ω_1). The sample is measured again as (ω_2) after the application of the wind speed.

The weight of material loss during the process is determined from Equation 1. The mass of loss material serves as the basis for measuring the ash retention efficiency of the sample (Equations 2 and 3). Three series of test is conducted for each stipulated period to eliminate as many anomalies as possible. The same method of calculations and procedure is followed for all the considered ash dust suppressants and their volumetric concentration in this experiment. A stipulated time periods of 6 hours, 24 hours, 48 hours, and 72 hours were also considered for the experiment. This process helps to determine the ash retention efficiency per period and will serve as a determinant for the efficiency of the ash dust suppression agent when applied over time.

Chemical suppressant such as #1 surfactants and #2 polymers were added to water to form a solution, to help improve the efficiency of water as an ash dust suppression agent. This addition holds the water molecules together to enhance the bond between them making it more adhesive against external forces. For a productive solution of dust suppression agent, water and each of the surfactant needs to be mixed at a certain volumetric concentration of dilution for a perfect mixture in controlling the emission of fugitive ash dust. Different concentration of #1 surfactant was tested with water to form a solution of 500 ml. The effectiveness of each dilution was tested, and the optimum value is selected as the volumetric concentration of the #1 surfactants solution for the experimental work. Volumetric concentrations of 0.05%, 1%, 2%, 3% and 4% of #1 surfactants were tested.

#2 polymers are the second surfactant considered for this experiment. This surfactant is mixed with water at a certain dilution of volumetric concentration to form a solution. This solution helps improve the efficiency of water to help form a better suppressant on the ash sample. Different concentrations of the #2 polymers were tested with water to form a solution of 500 ml. The effectiveness of each concentration is tested, and the optimum value is selected as the volumetric concentration of the #2 polymers for the experimental work. Volumetric concentrations of 2%, 3%, 5%, 10%, and 15% of the suppressant were created with water.

2.4. Calculation Methods

The parameters used in the equations for the experimental research is shown below.

t	Duration of sample under hot climate (hours)
d	Dilution rate for surfactants (%)
ω_p	Weight of plate (g)
ω_1	Weight of sample before blowing (g)
ω_2	Weight of sample after blowing (g)
$\Delta\omega$	Weight of sample loss (g)
r	Ash retention efficiency (%)
R	Average ash retention efficiency (%)

The weight loss ($\Delta\omega$) by an ash sample before and after the application of a wind speed of 55 km/h is calculated by Equation (1):

$$\Delta\omega\,(g) = \omega_1\,(g) - \omega_2\,(g) \qquad (1)$$

Where ω_1(g) is the weight of the ash sample with the application of ash suppression agent under a temperature season of 33 oC before applying a wind speed of 55 km/h and ω_2(g) is the weight of the ash samples remaining on the plate after the application of the wind velocity. Once the weight loss of the material is calculated, the ash retention efficiency can be calculated.

The ash retention efficiency (r) of each sample tested in the laboratory is dependent on the mass of the loss sample (Equation 2):

$$r\,(\%) = 1 - \Delta\omega/(\,\omega_1 - \omega_p\,) \qquad (2)$$

With the Ash retention efficiency of the sample, the average ash retention efficiency for three series of test, R is calculated as follows (Equation 3):

$$R\,(\%) = (r_1 + r_2 + r_3)\,/\,3 \qquad (3)$$

Where r_1, r_2 and r_3 are the ash retention efficiency for each experiment conducted for the ash sample within a series.

3. Results and Discussions

The results of the experiment demonstrate the use of suppressants as one of the effective ways of controlling the emission of fine solid particulate matter from ashes into the atmosphere. Water, #1 surfactants solution, and #2 polymers solution were tested during the research study. The baseline suppression agent considered for the control of fugitive ash dust into the air for this study was water.

The average ash retention efficiency for the ash sample with water as an ash dust suppression agent is shown in Table 1. The effect of water as an ash dust suppression agent over time in controlling the emission of fugitive dust is shown in Fig 5.

From the results provided the effectiveness of water decreases in accordance with time. The efficiency of water during the first 3 hours was effective and started reducing during 6 hours to 72 hours as the suppression agent gets more exposure to the hot climatic conditions. This process means that water dries up quickly under hot climate conditions, returning the ash sample back to the original state where no application of a control measure of a suppressant was implemented for the control of fugitive dust. Water as a suppressant contains molecules that are mostly separated from each other, reducing the bond of togetherness between the molecules.

Therefore, water is less efficient under hot climate and lacks the ability to retain its moisture content in the sample for longer duration when applied as an ash dust suppression agent, making the constant re-application of water as dust suppressing agent a requirement to control the fugitive ash dust from ashes. In improving upon the deficiency of water as an ash dust suppression agent, chemical suppressants are required.

Table 1. Average ash retention efficiency using water as an ash dust suppression agent

Trial (Water as a suppression agent)	ω_p(g)	ω_1 (g)	ω_2 (g)	$\Delta\omega$ (g)	*r (%)*	R (%)
W 01	429.10	450.51	449.47	1.04	95.14	
W 02	433.52	453.58	452.52	1.06	94.72	94.86
W 03	423.17	443.25	442.19	1.06	94.72	

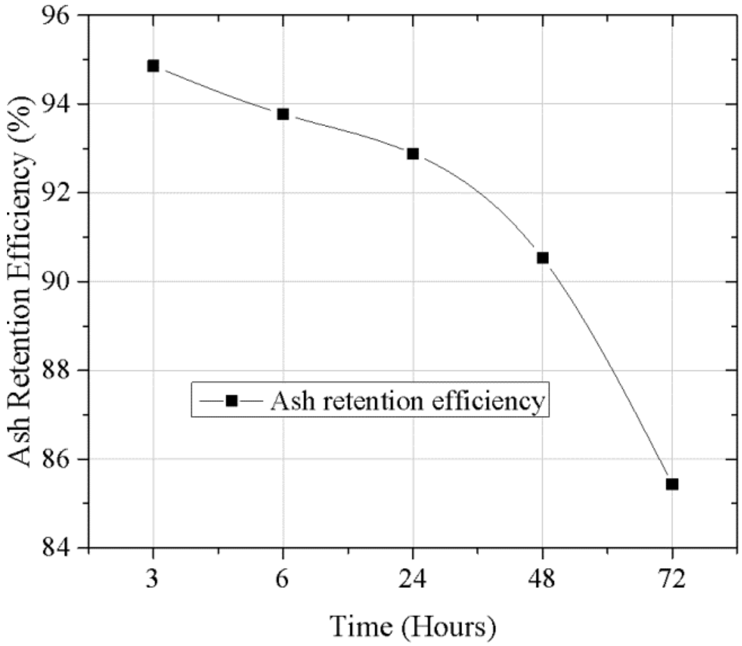

Fig 5. Effect of water as an ash dust suppression agent

Volumetric dilutions of each chemical suppressant were tested per the mixture with water through a preparatory process to form a solution. The optimum value of all the results is selected as the final dilution for the solution as shown in in

Table 2 and Table 3 . The corresponding ash sample retained per the volumetric concentration of each tested dilution is graphically shown in Figs 6 and 7.

#1 surfactants solution of 0.05% dilution was selected as the optimum solution. At this dilution, the solution will be efficient and economical during its application in controlling ashes emissions into the atmosphere. A 5% dilution concentration was selected as the optimum solution for #2 polymers solution. At this dilution, the solution will be efficient and economical during its application in controlling ashes emissions into the atmosphere.

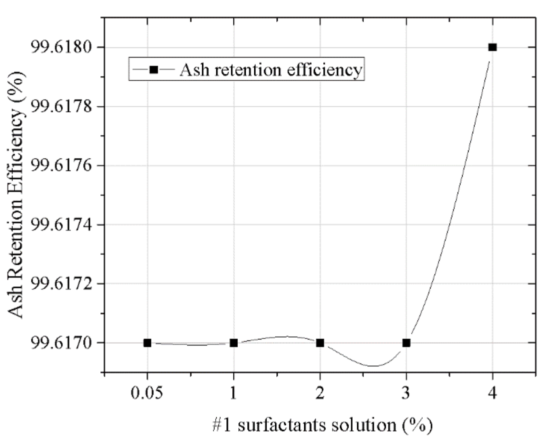

Fig 6. The relationship between of #1 surfactants solution and their ash retention efficiency

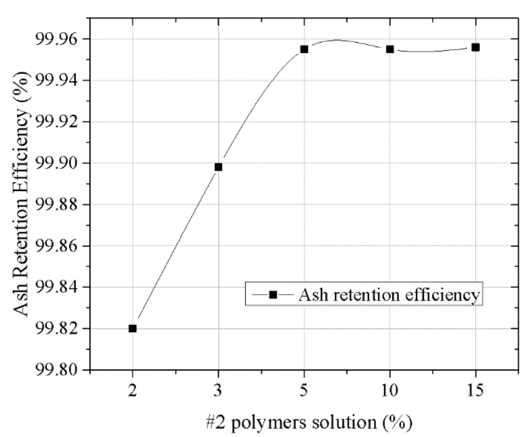

Fig 7. The relationship between #2 polymers solution and their ash retention efficiency

Table 4 and Table 5 show the results of the average ash sample retained after 3 hours of application of #1 surfactants solution and #2 polymers solution in controlling fugitive ash dust.

Table 2: Dilution concentration of #1 surfactants solution

Average Volumetric Concentration for #1 Surfactants Solution (%)	Average Ash Retention Efficiency (%)
0.05	99.62
1	99.62
2	99.62
3	99.62
4	99.62

Table 3: Dilution concentration of #2 polymers solution

Average Volumetric Concentration for #2 Surfactants Solution (%)	Average Ash Retention Efficiency (%)
2	99.82
3	99.90
5	99.95
10	99.95
15	99.96

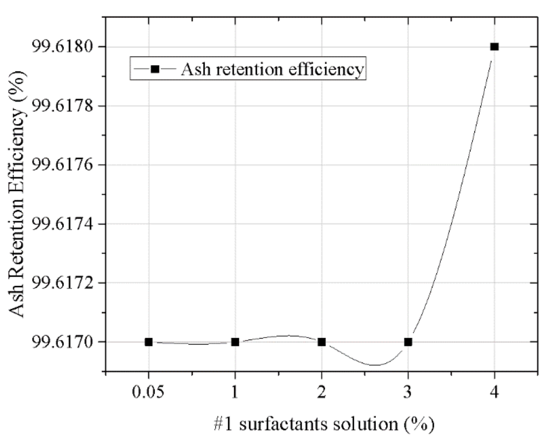

Fig 6. The relationship between of #1 surfactants solution and their ash retention efficiency

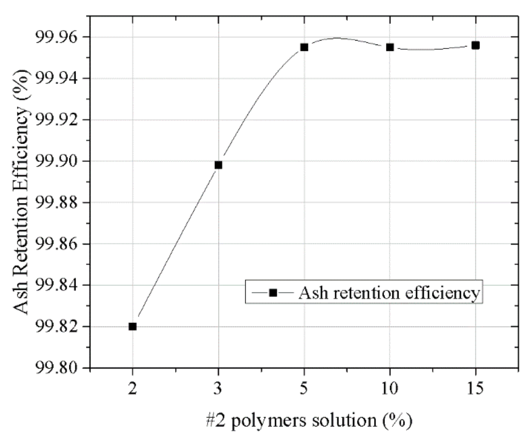

Fig 7. The relationship between #2 polymers solution and their ash retention efficiency

Table 4: Average ash retention efficiency for #1 surfactants solution

Trial (#1 surfactants solution for test)	ω_p (g)	d (%)	ω_1 (g)	$\omega_2$$(g)$	$\Delta\omega$ (g)	*r (%)*	R (%)
S 01	415.81	0.05	437.65	437.58	0.07	99.68	
S 02	430.45	0.05	451.21	451.12	0.09	99.57	99.63
S 03	456.86	0.05	476.93	476.86	0.07	99.65	

Table 5: Average ash retention efficiency for #2 polymers solution

Trial (#2 polymers solution for test)	ω_p (g)	d (%)	ω_1 (g)	ω_2 (g)	$\Delta\omega$ (g)	r (%)	R (%)
P 01	429.50	5.00	450.60	450.59	0.01	99.95	
P 02	425.10	5.00	447.60	447.57	0.03	99.87	99.92
P 03	434.70	5.00	456.30	456.29	0.01	99.95	

The result from Fig 8 shows that the application of #1 surfactants solution as an ash dust suppression agent performs better than water. This addition will help improve the efficiency of water to prevent the generation of fine solid particulate matter from the ash samples into the atmosphere for a longer duration when applied as a control mechanism for fugitive dust. The #1 surfactants solution at the initial stage of its application acts effectively by holding smaller particle sizes of the ashes together with the large particles, which helps prevent the emission of particles into the atmosphere when disturbed. After getting to the premium ash dust suppression ability, its efficiency on the sample starts to decrease. It has better ability in binding water molecules together cohesively and does not form a crusty surface above the sample when applied, making it easier to sweep and clean when disturbed by humans.

#2 polymers solution was also considered as a suppressant for the control of ash emissions into the atmosphere. Fig 9 shows the effect of #2 polymers and water as a suppression agent over time. The results show that the #2 polymers solution of dust suppression agent has the capability of holding fine solid particles of the ashes together after its application and until the third day.

This application shows how #2 polymers solution can bind water molecules together by help strengthening the bond by reducing the tension on the surface of the water. This property reduces the rate of evaporation under hot climate condition with time. The closer the molecule to molecule reaction, the lower the evaporation rate of the suppressant and the more effective the solution reacts with the fine and coarse ash samples by holding the two components together. The #2 polymers solution does not form crispy surfaces above the samples, which makes it easier to sweep when disturbed by waste management companies.

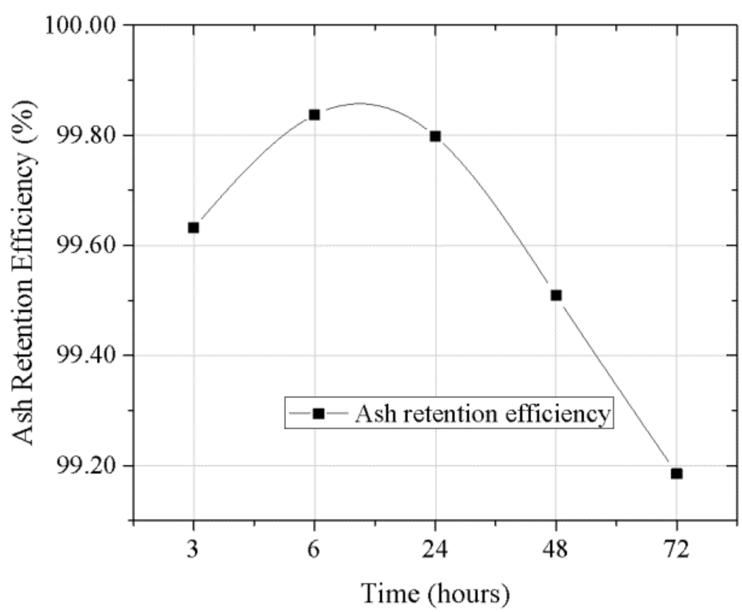

Fig 8. Effect of #1 surfactants solution as an ash dust suppression agent

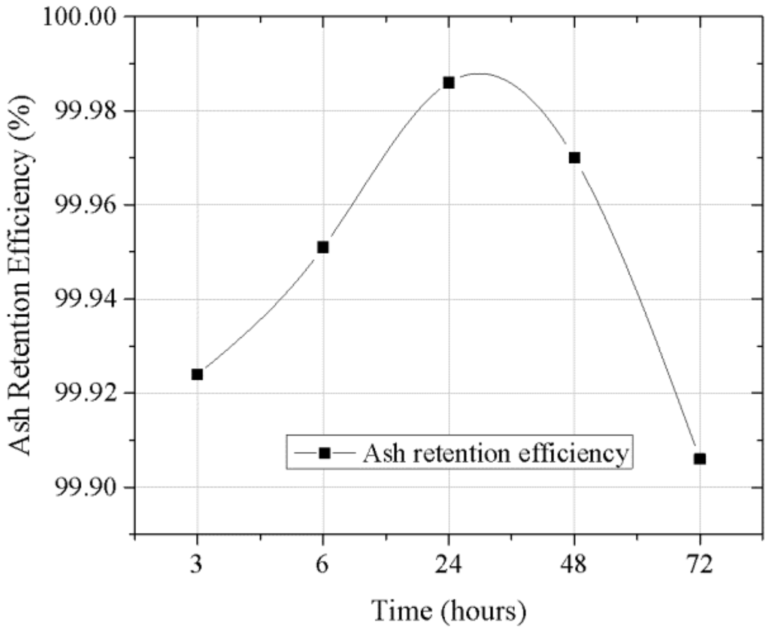

Fig 9. Effect of #2 polymers solution as an ash dust suppression agent

Ash retention efficiencies of all the tested suppressants are considered in selecting the most efficient ash dust suppression agent under a controlled hot climate condition. Fig 10 summarize the effect of all the considered dust suppression agents in this research. The result shows that #2 polymers solution is the most efficient ash dust suppression agent on fugitive ash dust emission from ash samples into the atmosphere compare to the others. #2 polymers solution has a high capacity of binding most of the water molecules together in forming an active suppressant for a longer duration against hot climate conditions as compared to the use of #1 surfactants solution and water as an ash dust suppression agent, based on their performance in terms efficiency.

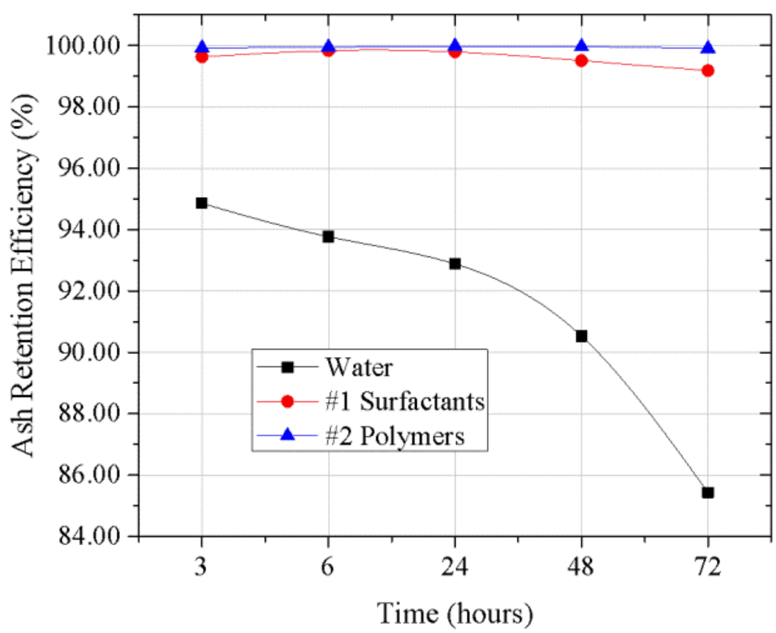

Fig 10. Effect of all ash dust suppressants on ash samples

4. Conclusions and Recommendations

The conclusive findings from the application of all the tested ash dust suppressants show:

1. Water at the initial stage of its application as an ash dust suppression agent worked fairly good on fugitive ash dust by showing an efficiency of 94.86 % of retained ash sample, but it decreased constantly with time and after 72 hours the efficiency drops to 85.44 %. This problem of depreciation of the ash retention efficiency with time shows that water works at the first; however it does not last long when applied as an ash dust suppressant.
2. #1 surfactants solution as an ash dust suppressant worked effectively at the initial stage of its application, retaining 99.63 % of the ash sample and maintained a fairly consistency retention efficiency even after 72 hours at 99.19 %. This solution works effectively for the control of fugitive ash dust on ash sample.
3. #2 polymers solution at the initial stage of its application as an ash dust suppression agent retained 99.92 % of ash samples on the plate and maintained this consistent retention even after 72 hours of its application at 99.90 %. This solution as an ash dust suppressant is highly effective in controlling the emission of fugitive ash dust into the atmosphere.
4. The inference of volumetric concentration of a chemical suppressant in a solution plays an important role on ash retention efficiency. Fig 6 shows that at an optimal concentration level, an increase in the concentration of a chemical suppressant have little or no impact on the ash retention efficiency. This implies that for each chemical suppressant an optimum concentration could be set up to avoid excessive suppressant addition to save cost.
5. The combined results from all the tested ash dust suppressants prove #2 polymers solution as the most efficient of all the three suppressants tested, followed by #1 surfactants solution, and water as the least efficient.
6. The use of chemical ash dust suppressants on ash emissions has been preliminary investigated. The results show how much more effective chemical suppressant prevents the emission of ash dust into the atmosphere compared to water. Hence, it is recommended to use chemical ash dust suppressants for the control of the fugitive ash dust in Fort McMurray.

It is recommended that conditions of climate factors such as humidity, precipitation, and others environmental parameters needs to be taken into consideration for future works.

5. Acknowledgment

We thank Roadtech Industries for the provision of the suppression agents and the ash samples for the research work.

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Human Factors and Human Error in Mining Industry: A Review and Lessons from Other Industries

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ABSTRACT

Human factors (HFs) play an important role in the mining and mineral industry; affecting operational and maintenance efficiency and safety. It is well-known—even considering the introduction of new technologies and automation in this sector—that a significantly large proportion of total human errors (HEs) occur during the operation and maintenance phase. The aim of this paper is to provide a comprehensive literature review of HF across several industries. From this review, the impact of HF on operation and maintenance will be summarized with a focus on what the mining industry is currently doing and what opportunities for additional efforts in the HF area are. Based on this review, future research directions and themes are identified.

1. Introduction

Over the last decades, the mining industry has focused on improving equipment, machinery and methods that have led to more advanced hardware and software, equipment with higher reliability and productivity, and other technological advancements. These actions have improved both safety and productivity as well as reduced casualties and maintenance workload. Although today's mining equipment and machinery are technologically advanced and highly reliable, the risk of accidents is still relatively high and the key performance indicators have not improved significantly compared to other industries (Sorensen, 2012). A prominent reason could be due to insignificant integration of human factors (HFs) as a part of the planning, operation, and maintenance activities. The current mining system is a people system, and inevitably HF/human error (HE) figure prominently in all aspect of this industry. Even the most advanced technologies and innovations require operators and maintainers with significant knowledge and skills, which could increase the potential for HE.

There are several methods developed for understanding the HF and HE contributing to industrial activities. Their application in operation and maintenance context has been largely advanced, predominantly in aviation and nuclear power industries.

This paper reviews current efforts in the mining, aviation, and nuclear industries for detecting, reporting, and managing HEs and HFs. An assessment of the suitability of approaches used in other industries for the mining industry is given and recommendations for next steps in improving how HFs and HEs are managed in the mining industry is given.

This paper, in its entirety, has been submitted for publication in CIM Journal.

2. Human Error

Generally, HE is defined as the failure to complete a required task (or execute a forbidden action) that could lead to the interruption of normal scheduled actions, damage to assets or compromise safety (Reason, 1990; Amalberti, 2001; Wiegmann & Shappell, 2003; Dhillon & Liu, 2006). Reason (1990) defined error as "a generic term to encompass all those occasions in which a planned sequence of mental or physical activities fails to achieve its intended out-come." Woods, Dekker, Cook, Johannesen, and Sarter (2010) defined error as "causal attribution of the psychology and sociology of an event." Papic and Kovacevic (2016) defined error as "failure (omission, unsuccessful attempt) to execute a required function, wrong decision in a response to certain problem, performing of function that shouldn't be executed, unsuccessful in recognition (observation, revealing) of a dangerous condition that requires corrective measures, bad timing and bad response to unpredicted circumstances."

HE has only been studied in the last 60 years (Dhillon & Liu, 2006). In general, the literature presents discussions of HE with minimal technical analysis and seems to be an under-researched area and not understood fully (Saward & Stanton, 2015). For the reader interested in a general discussion see Reason (1990), Perrow (1999), Wiegmann and Shappell (2003), Flin, O'Connor, and Crichton (2008), and Woods et al. (2010).

HE has been considered inevitable (Reason 1990; Maurino, Reason, Johnston, & Lee, 1998; Perrow 1999; Wiegmann & Shappell, 2003; Woods et al., 2010); and for instance in the aviation industry, it is associated with 70 to 90% of accidents (Hollnagel, 1993; Adams, 2006; Begur & Ashok Babu, 2016). Civil Aviation Authority (CAA) Safety Regulation Group (2002) stating: "It is an unequivocal fact that whenever men and women are involved in an activity, HE will occur at some point."

The poor condition of the working area (inadequate lighting, high noise levels), insufficient training or skills of operators, improper tools, poor equipment design and poorly written equipment maintenance procedures, and complicated operating processes have been recognized as some of the main reasons for the occurrence of HE (Dhillon & Liu, 2006). Dhillon (1986) classified HE into six categories:

1. Operating errors;
2. Assembly errors;
3. Design errors;
4. Inspection errors;
5. Installation errors; and
6. Maintenance errors.

Additionally, HE consequences are not always immediate and sometimes they may have hidden, undetected consequences which can lead to a latent error condition and delayed undesired outcome(s).

3. Human Error and Human Factor in Mining and Mineral Industry

The 'minerals industry' generally refers to a group of activities related to mining (minerals extraction), their processing and transportation (Horberry, Burgess-Limerick, & Fuller, 2013). The mining and mineral industry is one of the largest worldwide employer and key revenue earner; for example, mining contributed C$56 billion to Canada's Gross Domestic Product in 2015 (Energy and Mines Ministers' Conference, 2016).

Traditionally, mining is considered as an inherently high-risk industry. Nevertheless, the introduction of new technology and an increased concern for safety has helped to reach noticeable decreases in incident and injury rates over the last several years. In an effort to speed up this process, the HFs associated with operation and maintenance need to be addressed (Patterson, 2009). HE is present in mining and mineral industry operation and maintenance. It is an important factor influencing the safety success and effectiveness of operation and maintenance tasks and it can have undesired consequences if errors pass undetected and uncorrected.

The economy has always had a direct influence on the amount of attention which organizations and governments have in mining HF and ergonomic. For example, the 1980s virtual collapse of the coal industry in the UK caused a drop in the amount of British work in mining HF/HE (Simpson, Horberry, & Joy, 2009).

In the literature, with some overlap, HFs and HEs generally fall into the following five categories:

1. Safety and ergonomic related risks
2. Injuries and accidents
3. Mining equipment
4. Automation and new technologies
5. Mineral processing plants.

3.1. Safety and ergonomics

Morgan (1988) organized information to provide a step-by-step guide to developing and upgrading a program for safety and technical training for cement plant workers. Mason (1996) described an attitude survey of electricians in a coalfield to improve electricians' safety. Burgess-Limerick and Steiner (2006) presented several possible controlling measures such as hydraulic cable reelers; handrails on continuous miners (CM) platforms; redesign of CM platforms and bolting rigs to reduce reach distances during drilling and bolting; improvements to guarding of bolting controls.

Badri, Nadeau, and Gbodossou (2011) proposed a new concept, called "hazard concentration", based on the number of hazards and their influence. The method calculates a weight for each category of hazard related to an undesirable event by analytic hierarchy process (AHP) method to integrate of occupational health and safety (OHS) into risk management in an open-pit mining project in Quebec, Canada. The result of their project helped the company to choose a suitable accident prevention strategy for its operational activities. Later, Badri Nadeau, and Gbodossou (2013) developed a new approach based on their "hazard concentration" concept and AHP to risk management in mining projects. They constructed a database of about 250 potential hazards in an underground gold mine in Quebec, Canada. They showed the importance of considering OHS in all operational activities of the mine.

Burgess-Limerick, Joy, Cooke, and Horberry (2012) developed the operability and maintainability analysis technique (OMAT) technique for analyzing risks associated with operation and maintenance tasks, for the purpose of engaging with mining equipment manufacturers to accelerate improvements in the safe design of mining equipment. Horberry, Xiao, Fuller, and Cliff (2013) investigated challenges associated with information collection and management during underground coal mining emergencies from a human-centered perspective. They looked at decision making deficiencies in incident management teams, and organizational issues related to mining control rooms during emergencies to highlight the role of HF in mining emergency management. Nadeau, Badri, Wells, Neumann, Kenny, and Morrison (2013) outlined the challenges faced by deep mining operations for determining how to ensure safe and sustainable working environments. They argued designing new intelligent personal protective equipment that considers HFs could be a solution.

Ergonomics generaly defines as fitting a job to a worker; Torma-Krajewski, Steiner, Lewis, Gust, and Johnson (2007) presented the results from the implementation of an ergonomics process designed to identify and reduce exposures to ergonomic risk factors found in a US surface coal mine. They reported that mechanics and heavy equipment operators had the most concern about ergonomic. Torma-Krajewski and Lehman (2008) presented several examples of task-specific interventions that helped to reduce exposure to risk factors through implementing an ergonomics process to address exposure to risk factors that may result in musculoskeletal disorders or other types of injuries/ illnesses. Their work was a joint research project conducted by the US National Institute for Occupational Safety and Health (NIOSH) and a private mining company. Torma-Krajewski and Burgess-Limerick (2009) presented three case studies describing the steps that three mining companies in the US had taken to apply ergonomics to lower worker exposure to risk factors and musculoskeletal disorders (MSDs) and improve productivity.

3.2. Injuries and accidents

Burgess-Limerick, Straker, Pollock, Dennis, Leveritt, and Johnson (2007) implemented the participative ergonomics for manual tasks (PErforM) program at four Australian underground coal mines to facilitate ongoing miner participation in reducing injury risks associated with manual tasks. They presented several examples of the risk assessments undertaken and resulting potential control suggestions; and discussed the lessons learned. Paul and Maiti (2007) investigated the role of behavioral factors in underground mine's accidents and incidents. By caring out the study in two different coal mines in India they concluded that the group of workers who had experienced an in-jobsite accident were less satisfied with the job and more negatively affected compared to the workers without accidents.

Ruckart and Burgess (2007) analyzed data from the hazardous substances emergency events surveillance (HSEES) system for the period of 1996–2003 and concluded that HE-related events in mining and manufacturing resulted in almost four times as many events with victims and almost three times as many events with evacuations compared with events where HE was not a contributing factor, and also the night shift had no apparent influence on the events attributable to HE. Reardon, Heberger, and Dempsey (2014) reviewed U.S. mining maintenance and repair fatal reports (2002–2011) and developed a classification system to identify patterns and contributing human and non-HFs in fatalities during maintenance and repair operations in mining. They suggested several potential interventions to reduce fatality occurrences for both coal and metal/nonmetal mines. Sanmiquel, Rossell, and Vintró (2015) analyzed 70,000 occupational accidents and fatality reports between 2003 and 2012 in the Spanish mining sector using statistical methods such as Bayesian classifiers, decision trees or contingency tables to identify behavioral patterns. From the identified behavioral patterns, they developed potential prevention policies to decrease injuries and fatalities.

Cloug (2015) presented that there is a relationship between a rise in the fatality rate in the Australian mining industry over the last few years and a fall in commodity prices.

- *Human factor analysis and classification system (HFACS)*

The human factor analysis and classification system (HFACS) is a well-known framework for analyzing and classifying the underlying HFs associated with accidents and incidents. It has been applied in the aviation industry for many years (Wiegmann & Shappell, 2001; Wiegmann, Shappell, Boquet, Detwiler, Holcomb, & Faaborg, 2005; Tvaryanas & Thompson, 2008; Daramola, 2014). The original HFACS, contained 19 categories. These are placed in one of four levels including: unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences. Each tier is dependent on the previous one and factors are assumed to progress from active to latent conditions as they progress up the hierarchy from unsafe acts to organizational influences.

HFACS has been modified and applied in several areas. For example, to investigate railway accidents (i.e., HFACS-RR) (Baysari, McIntosh, & Wilson, 2008; Reinach & Viale, 2006; Kim, Baek, & Yoon, 2010), to assess the factors disturbing performance in a hospital operating room

(ElBardissi, Wiegmann, Dearani, Daly, & Sundt, 2007), and to improve patients safety (Milligan, 2007). Patterson and Shappell (2010) used HFACS method to analyze 508 incident and accident cases from across the state of Queensland, Australia to identify HF trends and system deficiencies within mining. They concluded that while the original HFACS method is valid for applying in aviation accidents, the nomenclature and examples within some of the causal category are not compatible with the mining industry. Therefore, they modified the original HFACS framework and developed a new HFACS-Mining Industry (HFACS-MI) framework (Table 1).

Lenné, Salmon, Liu, and Trotter (2012) analyzed 263 significant mining incidents in Australia across 2007–2008 using HFACS. They recommended focusing on HFACS categories at the higher levels such as organizational climate, planned inadequate operations, and inadequate supervision to reduce the number of unsafe acts at operational level. Furthermore, several researches have been done in China, mainly in coal mine section, to investigate mine accidents and safety system deficiencies (Jian-wei & Wen-yu, 2011; Chen, Yin, Zeng, Li, & Li, 2014; Zhao, Li, & Zeng, 2014; Xie, Yang, & Xu, 2015).

3.3. Mining equipment

Burgess-Limerick and Steiner (2006) investigated 959 injuries between 2002 and 2005 associated with CMs, shuttle cars (SCs), load–haul–dump machines and personnel transport vehicles (PT) in New South Wales underground coal mines to determine opportunities for controlling injury risks. They found that the most common work activities that let to injuries were: “strain while handling CM cable (96 injuries); caught between or struck by moving parts while bolting on a CM (86 injuries); strains while bolting on CM (54 injuries); and slipping off a CM during access, egress or other activity (60 injuries)”. Burgess-Limerick (2011) investigated 4,633 injuries occurring in underground coal mines between 2005 to 2008 in New South Wales (Australia) to identify opportunities for controlling equipment related injuries. He concluded that in 46% of injuries, equipment (continuous miner (12%), bolting machines (6%), LHD (8%), longwall (7%), personnel transport (4%), shuttle car (3%), and the rest (6%)) were involved. There were several high potential consequence events reported during the period including: interactions between personnel and mobile equipment; interactions between personnel and longwall shield movements; and transport equipment collisions. He suggested a series of possible short-term control measures for these risks.

Horberry et al. (2012) presented three case studies of HFs, focused on: reducing risks; developing emergency response management systems; and the value of participatory ergonomics in improving the design of mining equipment. They showed that properly dealing with HF is a key part in any sustainability initiative. In another study, Horberry (2012) reviewed the present technologies and the possible HFs issues associated with them and presented a four-stage research and development process to increase the safety and health benefits for operators of new technologies.

Papic and Kovacevic (2016) used a combination of causes-effect diagram, 5 Why? technique and event tree analysis to improve mining machines maintenance effectiveness. They used “Causes-effect diagram” and “5 Why?” technique to detect and categorize HFs/HEs that affect the results of the mining machines maintenance operation. They suggested to (1) use a proactive approach for solving potential HF problems in mining machines maintenance, (2) use the system of error proofing or Poka Yoke (Shingo, 1986) for HE proofing, and (3) providing training in the area of HF to reduce the number of errors in mining machine maintenance.

3.4. Automation and new technologies

Tichon and Burgess-Limerick (2009) reported several experiments on the implementation of virtual reality (VR) as a medium for safety related training in the mining industry and discussed a range of associated issues. They concluded that novice drivers’ hazard perception abilities and maintenance inspection tasks can be improved via training in a VR environment.

Table 1. HFACS and (*HFACS-MI)

Outside factors*	Regulatory Factors		Government regulations and policies effects on the mine's operation, health, and safety.
	Other		Society, economic, and environmental concerns effects on the health and safety of a mine site.
Organizational influences	Organizational climate		Prevailing atmosphere/vision within the organization (e.g., policies and culture).
	Operational process		Formal process by which the vision of an organization is carried out (e.g., operations and procedures).
	Resource management		How human, monetary, and equipment resources necessary to carry out the vision are managed.
Unsafe supervision	Inadequate supervision (leadership*)		Oversight and management of personnel and resources.
	Planned inappropriate operations		Management and work assignment (e.g., aspects of risk management, crew pairing, and operational tempo).
	Failed to correct known problems		Deficiencies related safety areas are ''known'' to the supervisor, and yet are allowed to continue uncorrected.
	Supervisory violations (Leadership Violation*)		The willful disregard for existing rules, regulations, instructions, or standard operating procedures by management during the course of their duties
Preconditions for unsafe acts	Environmental factors	Technological	This category encompasses a variety of issues including the design of equipment and controls, display/interface characteristics, checklist layouts, task factors and automation
		Physical	Included are both the operational setting (e.g., weather, altitude, terrain) and the ambient environment, such as heat, vibration, lighting and toxins
	Condition of operators	Adverse mental states	Acute psychological and/or mental conditions that negatively affect performance such as mental fatigue, pernicious attitudes, and misplaced motivation
		Adverse physiological states	Acute medical and/or physiological conditions that preclude safe operations such as illness, intoxication, and pharmacological and medical abnormalities known to affect performance
		Physical/ mental limitations crew	Permanent physical/mental disabilities that may adversely impact performance such as poor vision, lack of physical strength, mental aptitude, general knowledge, and a variety of other chronic mental illnesses
	Personnel factors	Crew resource management	A variety of communication, coordination, and teamwork issues that affect performance
		Personal readiness	Off-duty activities required to perform optimally on the job such as adhering to crew rest requirements, alcohol restrictions, and other off-duty mandates
Unsafe acts	Errors	Decision errors	These ''thinking'' errors represent conscious, goal-intended behavior that proceeds as designed, yet the plan proves inadequate or inappropriate for the situation.
		Skill-based errors	Highly practiced behavior that occurs with little or no conscious thought.
		Perceptual errors	These errors arise when sensory input is degraded, as is often the case when flying at night, in poor weather, or in otherwise visually impoverished environments.
	Violations	Routine	Often referred to as ''bending the rules''.
		Exceptional	Isolated departures from authority, neither typical of the individual nor condoned by management

Also, Tichon et al. (2011) reviewed the evidence for the value of VR as a medium for safety related training in mining. They argued the need of a large scale, systematic, assessment of the results of safety related training via virtual mining environments for future training. Later, Pedram, Perez, and Dowsett (2014) evaluated the impact of VR based training sessions on operators performance, safety standards, and mine productivity and used a cost benefit analysis to investigate the added-value of the VR. In another study, Alem, Huang, and Tecchia (2011), as part of a human system integration project within the CSIRO Minerals Down Under Research Flagship, presented a remote guiding system called HandsOnVideo to support and help a mobile local worker in maintaining complex equipment in mine sites remotely. They tested the usability of the system in a real industry situation.

Lynas and Horberry (2010) presented a literature review and a database of existing and emerging technologies of available automated mining equipment. They used this to explore how new technologies can be developed in ways that take into account HFs to determine the required skills and cognitive capabilities to operate or maintain the new technology for the purpose of developing an optimal interface design to eliminate performance gaps. They concluded deskilling of the operators and maintainer, over-reliance on the technology by operators, poor operator acceptance of new technologies, and poor HFs design of equipment interfaces are real problems. In another study (Lynas & Horberry, 2011a), they discussed lessons related to the impact of HF in automation learned from other industries. They argued several potential problems and their solutions. Also, Lynas and Horberry (2011b) review HFs and ergonomics (HF/E) work in mining and then investigated the emerging trends and HF/E issues associated with automated mining in Australia through a semi-structured interview process. They concluded that there are several issues such as automation, safe design, and workforce skill requirements and organizational issues related to HF/E in the mining industry.

Horberry and Lynas (2012) investigated operator interaction with automated mining equipment by preparing a database that considers both existing and emerging technologies. They used this to analyze the main HF issues for such technology. Recently, Horberry, Burgess-Limerick, and Steiner (2016) introduced the application of human centered design (HCD) in the mining industry and explained the benefits of a HCD approach and several successful examples in this industry.

3.5. Mineral processing plant

Li, McKee, Horberry, and Powell (2011) investigated the current status of control room operators at two different types of Australian mineral processing plants from a HFs perspective to explore the underlying difficulties in their workplace. They concluded developing effective human-machine interfaces (HMI) and alarms, improving operator training, and optimizing organizational factors are key elements to improve integration of operators and technologies. Later, Li, Powell, and Horberry (2012) investigated the status of control room operations in two types of mineral industry in Australia and explored the HF and underlying barriers in the operators' work environment. They concluded that poorly designed HMI and alarms, insufficient operator training, and inappropriate task allocations are among deficiencies in the current information and organizational environments constraining operator control ability.

Figs 1 and 2, illustrate the considered factor and area of study. Table 2 summarizes year of study and country of origin where the study was done.

Table 3 presents a classification of published papers on HF in mining and mineral industry.

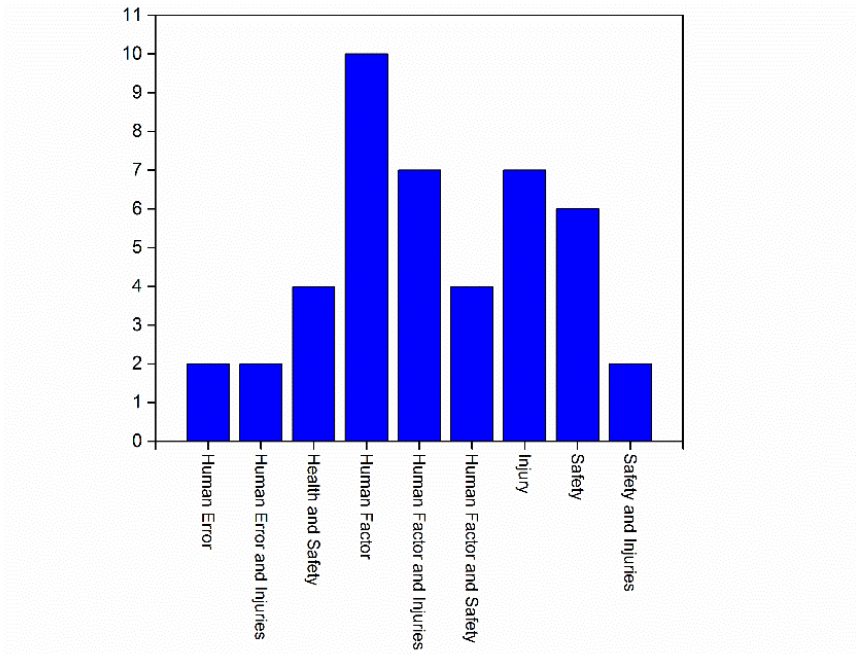

Fig 1. Published papers corresponding to considered factor in mining industry

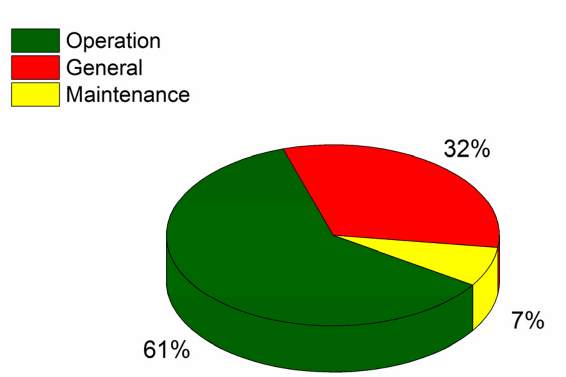

Fig 2. Published papers corresponding to the area of study in mining industry

Table 2. Number of the published papers and country of origin

Year	Australia	China	USA	Canada	UK	India	South Africa	Turkey	Spain	Serbia
1974			1							
1998	1									
2006	1									
2007	1		3		1	1				
2008			1							
2010	3	1					1			
2011	6	2		1						
2012	6	1	1							
2013	1			2				1		
2014	1	2	1							
2015		2							1	
2016	1									1
Total	**21**	**8**	**7**	**3**	**1**	**1**	**1**	**1**	**1**	**1**

Table 3. Summary of published papers about the effect of HF and HE in the mining and mineral industry

Reference	Scope	HF	HE	Safety/health	Accidents/ injuries	Country	Mining method	Operation/ maintenance
Lawrence (1974)	Injury data analysis		Accident causes		HE	USA	Underground mining	General
Mitchell, Driscoll, and Harrison (1998)	Injury data analysis				Work-related fatalities	Australia	General	General
Burgess-Limerick and Steiner (2006)	Injury data analysis				Injuries associated with mining equipment	Australia	Underground mining	Operation
Burgess-Limerick et al. (2007)	Reduce operation injury				Participative ergonomics for manual tasks (PErforM)	Australia	Underground mining	Operation
Ruckart and Burgess (2007)	Accident data analysis		Time of occurrence			USA	General	General
Torma-Krajewski et al. (2007)	Reduce exposure to risk			Implementation of an ergonomics process		USA	Surface Mining	Operation
Coleman and Kerkering (2007)	Injury data analysis	Safety, injuries, and lost workdays		Defining lost workdays as indicators of risk		USA	General	Operation
Paul and Maiti (2007)	Safety management			The role of behavioral factors		India	Underground mining	Operation
Torma-Krajewski and Lehman (2008)	Reduce exposure to risk			Ergonomic interventions		USA	Surface mining	Operation

Table 3. Continued

Reference	Scope	HF	HE	Safety/health		Accidents/ injuries	Country	Mining method
Burgess-Limerick, Krupenia, Zupanc, Wallis, and Steiner (2010)	Equipment design		Reducing control selection errors			Australia	Underground mining	Operation
Lynas and Horberry (2010)	Automation	HF challenges of automated mining equipment				Australia	General	Operation
Patterson and Shappell (2010)	Accident data analysis				HFACS	Australia	General	General
Green, Bosscha, Candy, Hlophe, Coetzee, and Brink (2010)	Automation			Improving safety using robots		South Africa	General	Operation
Lan and Qiao (2010)	Accident data analysis		HEs reliability using gray relational theory			China	Underground mining	General
Alem et al. (2011)	Automation	Remote collaboration				Australia	General	Maintenance
Badri et al. (2011)	Reduce exposure to risk			Integration of OHS into risk management		Canada	Surface mining	Operation
Burgess-Limerick and Steiner (2006)	Accident data analysis				Equipment associated injuries	Australia	Underground mining	Operation

Table 3. Continued

Reference	Scope	HF	HE	Safety/health	Accidents/ injuries	Country	Mining method	Reference
Li et al. (2011)	Mineral process control room operation	Human machine interface				Australia	Mineral processing	Operation
Lynas and Horberry (2011a)	Automation	HF issues with automated mining equipment				Australia	General	General
Lynas and Horberry (2011b)	Automation	Review of Australian HF research and stakeholder opinions				Australia	General	Operation
Tichon and Burgess-Limerick (2011)	Reduce exposure to risk Related to training in mining			A review of virtual reality as a medium		Australia	General	Operation
Jian-wei and Wen-yu (2011)	Safety analysis			HFACS, coal mine safety system deficiencies and unsafe acts		China	Underground Mining	Operation
Wu, Jiang, Cheng, Zuo, Lv, and Yao (2011)	Accident data analysis				Accident data analysis	China	Underground Mining	General
Burgess-Limerick et al. (2012)	Safety management			Safety improvement and injury prevention, OMAT		Australia	General	Operation

Table 3. Continued

Reference	Scope	HF	HE	Safety/health	Accidents/ injuries	Country	Mining method	Reference
Horberry (2012)	Automation			Review of benefits of new technologies in mining		Australia	General	Operation
Horberry et al. (2012)	Sustainability	The role of HF in a sustainable mineral industry				Australia	General	Operation
Lenné et al. (2012)	Accident data analysis				HFACS	Australia	General	Operation
Xilin Li et al. (2012)	Mineral process control room operation	Human-system integration				Australia	Mineral Processing	Operation
Drury, Porter, and Dempsey (2012)	Accident data analysis				Patterns in mining haul truck accidents	US	General	Operation
Chen, Qi, Long, and Zhang (2012)	Accident data analysis				Characteristics of HFs	china	General	Operation
Badri et al. (2013)	Risk management			AHP, OHS		Canada	Underground mining	Operation
Horberry et al. (2013)	Mining emergency management	The role of HF and ergonomics				Australia	Underground mining	Operation
Onder (2013)	Accidents data analysis				Logistic regression models	turkey	Surface mining	Operation
Reardon et al. (2014)	Accidents data analysis				Hazard classification	US	General	Maintenance

Table 3. Continued

Reference	Scope	HF	HE	Safety/health	Accidents/ injuries	Country	Mining method	Reference
Horberry (2014)	Equipment design	Safety in design				Australia	General	General
Zhao et al. (2014)	Accident data analysis				HFACS	China	Underground mining	Operation
Chen et al. (2014)	Accident data analysis				HFACS, Bayesian network	China	Underground mining	Operation
Sanmiquel et al. (2015)	Accident data analysis				Bayesian network, data mining	Spain	General	Operation
Xie et al. (2015)	Safety analysis			HFACS, SPA set pair analysis		China	General	Operation
Gui and Chun (2015)	Accident data analysis				Research on responsible person	China	Underground Mining	Operation
Papic and Kovacevic (2016)	Equipment maintenance	Cause-effect diagram and event tree analysis				Serbia	General	Maintenance
Horberry et al. (2016)	Equipment design	Human-centered design				Australia	General	General

4. Aviation, Nuclear, and other industries

Aviation and nuclear industries have done a significant amount of research to investigate the impacts of HF/HE in their maintenance activities (B.S. Dhillon & Liu, 2006), and still continue their efforts to overcome many remaining and newly introduced HF/HE related challenges (Begur & Ashok Babu, 2016).

To demonstrate the progression of methodologies and theories, in the rest of this section, the contributing HF and HE in maintenance and operation activities are reviewed separately.

4.1. Maintenance

Because of the complex nature of the procedures, including removal and replacement of different components, detecting faults which in many cases are uncommon and difficult to spot and require high levels of attention and expertise, tough working conditions, difficult ergonomic body positions, and regularly under time pressure, maintenance tasks are vulnerable to HE (Pennie, Brook-Carter, & Gibson, 2007).

HEs in maintenance has been a contributory factor in several high-profile accidents across different industries (Pennie et al., 2007). HE in aircraft maintenance is cited for 15% to 20% of aviation misshapes (Manwaring, Conway, & Garrett, 1998; Patankar & Taylor, 2004; Rashid, Place, & Braithwaite, 2013; Begur & Ashok Babu, 2016) and at least 70% of naval aviation safety occurrences in UK (Saward & Stanton, 2015).

4.1.1. Aviation

Drury (1991) offered a taxonomy and means of eliminating maintenance errors in the aviation industry, and later, Graeber and Marx (1993) showed the economic aspect of maintenance error.

Shepherd and Johnson (1995) described several research products that are currently improving safety and efficiency in maintenance applications worldwide. Hobbs and Williamson (1995) investigated the type of errors made by maintainers in corporations with an air carrier in the Asia-pacific region. Havard (1996) presented British Airways' initiatives regarding HFs. Kania (1996) investigated casual factors contributing to HE. O'Connor and Bacchi (1997) presented an error taxonomy to classifying HE in maintenance and dispatch operations. Witts (1997) discussed the impact of HF on aircraft maintenance in Air UK Engineering. Reason (1997) claimed that maintenance-related error is one of the largest single HFs problems in modern aircraft systems. Ford (1997) discussed the impact of HE in airline maintenance on safety and discussed what is required to lessen the safety inadequacies. Shepherd and Kraus (1997) investigated the effect of several factors such as technician teaming and advanced technology, and evaluation of simplified English on the performance of maintainers. Amalberti and Wioland (1997) argued the relationship between aviation accidents and errors and the systemic safety approach for large socio-technical systems. Nelson, Haney, Ostrom, and Richards (1997) presented a structured method to identify, assess and prevent HE in space operation which can be applied. Koli, Chervak, and Drury (1998) developed two HF audit methods in aircraft inspection and maintenance process tasks to detect the human-system mismatches that can lead to errors, they are inspection audit and maintenance audit which can be used either in paper version or on a portable computer. McGrath (1999) with regard to airworthiness and safety, discussed aviation management imperatives to improve the professionalism of the field personnel's culture. Latorella and Prabhu (2000) reviewed current trends in dealing with HE in aviation maintenance and inspection. Wenner and Drury (2000) presented a methodology for analyzing the HEs' reports. Reason (2000) presented a job-oriented approach to determine the human performance problem in aviation. Shepherd (2002) explained actions regarding aircraft maintenance and inspection HFs.

Strauch and Sandler (1984) article discuss the important role of the aviation maintenance technician (AMT) in the safe operation of an aviation system. Hibit and Marx (1994) anticipated that using maintenance error decision aid (MEDA) can improve safety and maintenance system reliability. Allen and Rankin (1995) evaluated MEDA through a field test. Rankin, Hibit, Allen, and Sargent (2000) also evaluated the development and implication of MEDA to determine and eliminate the factors that contribute to maintenance error. Bao and Ding (2014) used MEDA and correspondence analysis methods to analysis maintenance error in 3,783 Aviation Safety Reporting System incident reports submitted during the period of January 1, 2008 to

December 31, 2008. They argued that a large proportion of maintenance errors has been initiated by both maintenance personnel and non-maintenance personnel, and individual-related factors and management-related factors are the most common reasons for maintenance error.

Liang, Lin, Hwang, Wang, and Patterson (2010) developed an on-line maintenance assistance platform (on-line MAP) for technicians to remove HE in performing aviation maintenance and inspection tasks. Chang and Wang (2010) determined nine significant human risk factors out of 77 preliminary and 46 primary risk factors in aircraft maintenance technicians by conduction an empirical study of Taiwan's airlines to improve maintenance operations. Atak and Kingma (2011) presented a case study about the safety culture of an aircraft maintenance organization and analyzed the various roles and the tensions between the quality assurance and maintenance management departments to stress the paradoxical relationship between safety and economic interests. Rashid et al. (2013) investigated the impact of human reliability on aviation maintenance safety and introduced a new model indicating the commencement and spread of critical maintenance HEs within aviation maintenance organizations. Cromie et al. (2013) described an initiative being utilized by a European aviation maintenance company to overcome the challenge of integrating human and organizational factors (HOF) training within a risk management context in a European aviation maintenance company. Chen and Huang (2014) introduced the Bayesian network (BN) approach to perform Human reliability analysis (HRA) in aviation maintenance visual inspection activities. Chen (2014) analyzed the characteristic, cause and mode of the aviation maintenance error to address appropriate management and control method for specific aviation maintenance HEs. Rashid, Place, and Braithwaite (2014) proposed aviation maintenance monitoring process; an integrated process to identify HE causal factors using fuzzy Analytic Network Process theory. Shanmugam and Robert (2015) reviewed and analyzed HFs in aircraft maintenance. They concluded that application of HF principals has created a great impact on the design of aircraft maintenance facilities, task cards and equipment, and these HF principals are applied to enhance the safety behavior in aviation maintenance workstation. Saward and Stanton (2015) described the nature and extend of individual latent situational error in naval aircraft maintenance by combining prospective memory, attentional monitoring, and schemas theories. Begur and Ashok Babu (2016) presented a method to collect and assess the data to analysis and reduce HFs in aircraft maintenance and improve the maintenance practices in order to decrease the number of aviation mishaps they might cause.

4.1.2. Nuclear power

Seminara and Parsons (1985) presented an overview of several HFs research conducted under the sponsorship of the electric power research institute (EPRI). They identified HFs problem areas and future research opportunities rather than provide direct solutions for deficiencies. Jacobsson and Svensson (1991) investigated psychosocial work demands of a maintenance group in a nuclear plant during the annual maintenance outage, based on a stress paradigm. They found that increased work strain, shiftwork including night work and reduced social support would have a negative impact on performance. Gertman (1992) presented a review of a mainframe version of a computer code for simulating maintainer performance. Pyy, Laakso, and Reiman (1997) investigated about 4400 HEs in nuclear power plant (NPP) maintenance between 1992 and 1994 to identify common cause failure mechanisms. He suggested that enhanced coordination and review, post-installation checking and start-up testing programs might decrease number of errors. Kim (1997) described the Korean-version of HPES (human performance enhancement system) program and the current status of CASHPES (computer-aided system for HPES) development to reduce HEs and to enhance human performance in nuclear power plants.

Nakatani, Nakagawa, Terashita, and Umeda (1997) proposed DIAS, a new method to evaluate the human interface design of nuclear power plant equipment from the viewpoint of HE in maintenance activities. Lee, Oh, Lee, and Sim (1997) presented several HFs research including the development of a HFs experimental facility; the development of an operator task simulation analyzer; and analysis of HE cases performed by the Korean Atomic Energy Research Institute. Sola et al. (1997) described an overview of the main activities carried out by CIEMAT (Spain Research Centre for Energy, Environment and Technology) in the nuclear power plant industry regarding HF. Huang and Zhang (1998) analyzed root causes and discussed protective measures with respect to safety for HE events in operating and maintenance activities at the Daya Bay

Nuclear Power Plant, China. Röwekamp and Berg (2000) analyzed the operational behavior of different fire protection features based on the examination of reported results of regular inspection and maintenance programs for German nuclear power plants. Antonovsky, Pollock, and Straker (2014) investigated 38 maintenance-related failures in the petroleum industry using a HF Investigation Tool (HFIT) based on Rasmussen's model of human malfunction to identify the role of HF. They concluded there are three frequent HFs contributing to the maintenance failures: assumption (79% of cases), design and maintenance (71%), and communication (66%).

4.2. Operation

Mogford (1997) introduced the Taxonomy of Unsafe Operations for accident investigation and human casual factor classification, including the condition of operators and supervisory error. Li, Baker, Grabowski, and Rebok (2001) investigated 329 major airline crashes, 1,627 commuter/air taxi crashes, and 27,935 general aviation crashes between 1983 to 1996 to determine the role of pilot error. They also investigated the probable relationship between pilot certificate rating, age, gender, and flight experience as measured in total flight time. Wiegmann and Shappell (2001) used HFACS for the first time to analyze the human causes of commercial aviation accidents between January 1990 and December 1996. They confirmed the viability of HFACS framework for use within the civil aviation arena. Hirotsu, Suzuki, Kojima, and Takano (2001) investigated all incidents in Nuclear power plants (NPPs) during last 31 years using multivariate analysis to find HE occurrence patterns in this industry. They concluded wrong unit/train/ component, slip due to inattentiveness, improper setting value, inappropriate action, misconnection or miswiring of terminals, insufficient tightening or inadequate fitting objects, and insufficient torque management were major HE types during maintenance. Additionally, Wrong unit/train/component, operational slip due to inattentiveness, and operational deviation or disorder were major HE types during operation.

Shorrock and Kirwan (2002) introduced TRACEr, a HE identification (HEI) technique, for the analysis of cognitive errors in air traffic control in the UK. Grech, Horberry, and Smith (2002) analyzed maritime accidents in order to identify the role of HE and Situation Awareness (SA). Their results revealed that loss of SA had a partial role in the majority of investigated maritime accidents. Khan, Amyotte, and DiMattia (2006) developed a new HE probability index (HEPI) for offshore operation based on the SLIM (success likelihood index methodology) to constrain the chances of HE occurrence and reduce the consequences of such errors through changes in training, design, safety systems and procedures, which would lead to a more error-tolerant design and operation.

Bellamy, Geyer, and Wilkinson (2008) analyzed a small sample of major chemical accidents to find logical patterns of associations which can be used in the applied contexts of inspection and auditing. The result of their work helps inspectors and chemical companies understand how HFs and safety management systems fit together.

5. Discussion and Conclusion

Years of study has proved that attention to HF and reducing HE is one of the best ways to enhance performance and reduce the risks of accidents and incidents.

Like the aviation industry, the mining industry needs to first identify major HF/HE related to its operation and maintenance activities. The next step is to quantify the economic aspects of them. Although, it seems difficult to address all HFs/HEs and their consequences, the final result would give professionals, researchers, and even managers an exact indicator of the influence of each HF/HE in their job activities. In addition to the possibility of revealing yet unseen HF/HE during this process, finding the magnitude of each HF/HE's economic impact can facilitate improvements by revealing and addressing the most critical factors.

Performance shaping factors (PSFs) are a number of direct or indirect factors and aspects of the task, person or environment that are likely to increase the chance of HE. They have been used in risk analysis in several industries, and are considered the major contributors to HE (Boring & Blackman, 2007; Broberg & Kolaczkowski, 2007). Therefore, to identify and reduce the HEs, it is necessary to further analyze the PSFs involved in mining and mineral operation and maintenance activities. The results of this type of study would help the mining industry to reduce HE and improve PSFs involved in their activities by considering a necessary change(s) to equipment, tools, or process, as well as changes in management approaches.

Additionally, cognitive biases which generally define as systematic patterns of deviation from norm or rationality in judgment (Haselton, Nettle, & Murray 2015) and their role in incidents and disasters, as well as how they alter decision making and lead to undesirable outcomes need to be investigated.

- ***HE probability assessment methods***

HE Probability (HEP) assessment methods for quantification of human reliability are an under researched area in the mining and mineral industry. Further studies to identify a suitable HEP method among the different available methods such as subjective judgment HEP methods [e.g., Absolute Probability Judgment (APJ), Paired Comparisons (PC), Success Likelihood Index Method (SLIM) (Embrey, Humphreys, Rosa, Kirwan, & Rea, 1984)] and AHP-SLIM or HE database methods [e.g., HE Assessment and Reduction Technique (HEART) (Williams, 1986), JEHDI, and THERP (Swain & Guttmann, 1983)] for each individual mining sector and activity can enable researchers and professionals in this industry to properly address the related issues.

- ***HFACS***

Fatalities and major accidents are not acceptable to the mining and mineral industry, and the role of HF and HE can help with the goal of eliminating them. In an effort to reduce the rate of accidents, the HFs associated with them needs to be addressed. Currently, despite a few mining and mineral industry accident analysis studies, there are no reports about the main HF and HE caused accidents and incidents in Europe and North America. More studies are needed to gain a better understanding of the systemic factors contributing to mining accidents, and to evaluate those organizational and supervisory failures that lead to HF and HE. The results would provide the information necessary to reduce mine accidents.

Additionally, despite the fact that HFACS has been approved as a practical method for investigating the role of HF in accidents and incidents, it suffers from some inherent deficiencies. HFACS analysis is based on accident reports. Reporting of an accident often involves subjectivity and filtering and the causal inference may be manipulated by the data collection method. Also, considering the different background, position, and level of education of people writing them, accident reports will differ in both content and format. More study is needed to create a comprehensive reporting form based on the HFACS method to enables people across the industry to writes universal, extensive, and detailed reports of the accidents and incidents. These pre-defined forms approach would prevent the loss of information for some aspect of incidents or accidents and would help ensure consistent analysis of data.

The final reporting system also facilitates analyzing accidents to look for logical patterns of associations. The idea is that once identified, the patterns can be used in the applied contexts of operation and maintenance. If the patterns can be found in practice they can be used to identify weaknesses that could cause major accidents. Similarly, the patterns can be used to understand accident causation during accident investigations.

- ***Automation and new technologies***

Increased interest in using automated mining equipment, ranging from in-vehicle assistance systems (such as collision detection or prevention) through to fully automated and ‘people-less’ equipment (Lynas & Horberry, 2010), has brought to attention the importance of HF. However, current studies show that the human related part of automation (e.g., skill level of staff to support the automation) has not developed at the same pace as the equipment technology, because it is required to provide operators and maintenance crew with new skills to operate and support these technologies (Lynas & Horberry, 2010).

It is shown that simultaneously working with several semi or fully automated machines which need human interaction is a potential environment for HE where the role of HF needs to be investigated. In such an environment, studying risk-taking behavior using risk-taking theories such as risk homeostasis theory (RHT) (Wilde, 1989) could emphasize the importance of motivational factors in interventions to reduce operational risk.

On the other hand, studies in other industries have shown that excessive levels of mental workload or performing physical work concurrently with a cognitive task may have a negative impact on operator performance by impairing mental processing or delaying information processing and it could trigger HEs (DiDomenico & Nussbaum, 2011; Ryu & Myung, 2005). An assessment of the effect of mental workload in modern semi or full automated mining and mineral industry environment can reveal important aspects of the design and evaluation of an occupational task.

Remotely located individuals working on operation and maintenance tasks and using virtual reality as a medium for operation simulation are two fast growing sectors in the mining industry. For instance, several systems have been developed to enable a maintenance expert to remotely guide a technician through repairing a piece of equipment (Alem et al., 2011; Karsenty, 1999). Also, utilizing virtual reality as a medium for operation simulation offers the opportunity to enhance operational skills such as problem-solving, and decision-making under stress, without exposing trainees or others to undesirable risks (Tichon & Burgess-Limerick, 2009). The exact potential of these new technologies for improving efficiency, productivity and safety by removing HE (skill-based errors, violations, inadequate supervision and etc.) during operation or maintenance tasks still needs to be evaluated.

6. References

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Comparison of Chemical Suppressants Under Different Atmospheric Temperatures for The Control of Fugitive Dust Emission on Mine Haul Roads

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ABSTRACT

Dust generated from haul roads poses a severe health and safety threat to mine sites. Traditionally, water has been applied on mine haul roads to control the dust. Although environmentally friendly, water lasts for a limited duration due to evaporation. Consequently, water has less longevity and requires consistent re-application, leading to an enormous waste of valuable water resources, especially in remote areas where most mine sites are located. One solution is to add chemical suppressant to water in mine sites. Despite many practical applications, there is a research gap for the effect of various atmosphere temperatures on the performance of chemical suppressants. The objective of this study is to investigate the role of different atmosphere temperature on the effectiveness of chemical suppressants to control mine haul road dust. In this study, water and selected chemical surfactants— salt, chloride free agents, polymers, and molasses—were tested experimentally for their dust retention efficiency under three different atmosphere temperatures within a time frame of 72 hours. Compared with water, salt solution, chloride free solution, polymer solution, and molasses solution achieved higher efficiencies than those of water. It is concluded that atmosphere temperatures play an important role in the effectiveness of chemical suppressants.

1. Introduction

Road dust generated through truck hauling in the mining industry is a severe hazard to the health of workers and the maintenance of roads and vehicles. Road dust usually contains silica and other heavy metals that when inhaled can lead to diseases such as lung cancer, abnormal kidney function, and rheumatoid arthritis (Cecala et al., 2012). Accounting for about 78% to 97% of the total amount of dust emitted into the atmosphere in surface mining operations, road dust mainly consists of solid particulate matters having smaller particle diameters (i.e., 2 μm – 75 μm) (Foley et al., 1996; Kavouras et al., 2009; Thompson and Visser, 2007). Dust emissions from road surfaces lead to soil erosion, which has an adverse effect on vehicles' travel times (Thompson and Visser, 2007). Moreover, deteriorated mine roads increase drivers' whole-body vibration and affect the performance of haul trucks, the way operational service vehicles handle materials, and mine productivity. The moving parts of the haul trucks, such as bearings and engines, may also be affected by the emitted solid particles, creating downtime in operational scheduling and an increase in vehicular maintenance costs (Organiscak and Randolph Reed, 2004).

This paper, in its entirety, has been submitted for publication in Atmospheric Pollution Research (APR).

A common road dust control method in the mining industry is to dampen the road with water (Kavouras et al., 2009; Thompson and Visser, 2007). Although environmentally friendly, this approach has a limited duration because water evaporates (Foley et al., 1996). As a result, water must be regularly reapplied, usually by frequent spraying, leading to a tremendous amount waste of valuable water resources, especially in remote areas, where most mine sites are located (Cecala et al., 2012; Kavouras et al., 2009; Thompson and Visser, 2007). In addition to water, using chemical surfactants to form a solution of chemical suppressants has been considered as a more effective method to control fugitive (DeLuca et al., 2012; FCM and NRC, 2005; Gillies et al., 1999). For example, some pilot studies have been done to determine how effective chemical suppressants are; they overviewed the duration and cost of using chemical suppressants on surface mine haul roads in some South African mines (Thompson and Visser, 2007).

A chemical suppressant as a control agent is formed by mixing water with an optimal volumetric concentration of surfactant (Samaha and Naggar, 1988). To date, the mining industry has used various chemical suppressants such as lignosulphonates products, salts, petroleum products, polymer emulsion products, and foaming agents to control fugitive dust on haul roads (Foley et al., 1996; Monjezi et al., 2009; Sanders et al., 2014; Shang et al., 2012). In general, previous research has shown that chemical suppressants provided better performance and greater longevity (Foley et al., 1996; Gillies et al., 1999; Kavouras et al., 2009; Thompson and Visser, 2007). Using chemical suppressants allows companies to generate higher revenues without having to increase their workforce (Cecala et al., 2012). However, atmospheric factors such temperature need to be considered when ensuring the efficacy of a chemical suppressant (Amponsah-Dacosta, 1997; Chiou and Tsai, 2001; Fitz and Bumiller, 2000). This is because temperature plays a critical role in the effectiveness of a chemical suppressant on mine haul roads (Chiou and Tsai, 2001), specifically on evaporation efficiency, which affects performance and longevity of the dust suppressants (Visser, 2013). For example, the effectiveness of different chemical suppressants was evaluated under hot atmospheric temperatures on unpaved roads in Chile, Australia, and the United States (Sanders et al., 2014; Valenzuela et al., 2014; Visser, 2013); however, these studies did not consider other atmospheric temperatures. So far, there is no guide for the comparative assessment analyses on dust control methods located in different climate zones. In particular, no research has been initiated on the evaluation of the effectiveness of chemical dust suppressants under different atmospheric temperatures.

In this research, four types of suppressants commonly used in the mining industry were chosen: a salt solution, chloride-free solution, polymer solution, and molasses solution. These suppressants were selected because unlike more traditional suppressant (i.e., water) have been used on a number of unpaved roads at different locations around the globe to achieve better results. For example, chloride salts, polymer emulsions, molasses, petroleum products and lignosulphonate products have been used on some unpaved roads in countries such as South Africa, Chile, India, and Sweden to achieve success in dust control (Edvardsson et al., 2011; Mishra and Jha, 2010; Thompson and Visser, 2007; Valenzuela et al., 2014). The first one is salt, which is cost effective, environmentally friendly, and easily accessible, and it works effectively in binding water molecules together to reduce the efficacy of evaporation under extreme weather conditions (i.e., dry and hot) (Amponsah-Dacosta, 1997; Cecala et al., 2012; Kavouras et al., 2009). Also, the chloride-free, polymer, and molasses solutions were selected because they perform efficiently and last longer as chemical suppressants in hot weather (Kavouras et al., 2009; Shang et al., 2012; Tran et al., 2008).

The objective of this study was to examine the effects of selected chemical dust suppressants on fugitive dust emission on haul roads at three different atmosphere temperatures (i.e., 35 ^{o}C, 15 ^{o}C, and -19 ^{o}C) mimicking hot, normal, and cold seasons. This research highlights the role of atmosphere temperature on the performance of four chemical dust suppressants commonly used in the mining industry. The research results will help curb haul road deterioration, maximize vehicular uptime, increase revenue generation, and assist in minimizing the threat of fugitive dust to workers' health and safety.

2. Experimental Details

2.1. Equipment and Materials

To mimic the hot season, a Despatch LLB series oven, model LBB1- 43A-1 with a maximum temperature of 204 ^oC, was used. A room thermostat was used to control the room temperature of 15 ^oC to represent the normal season. For the cold season, a heavy-duty freezer was used to maintain the temperature of -19 ^oC. A blower with a full capacity speed of more than 80 km/h was set up as a source of wind to trigger dust generation for the experiment.

As shown in Fig 1, a portion of 35 kg of soil sample was received from a local unpaved construction site in the City of Edmonton. Some of the characteristics of the soil sample are similar to characteristics of chernozemic soil found in the City of Fort McMurray, where most haul roads are constructed for oil sands mining (Crown and Twardy, 1975; SCWG, 1998). The soil sample used for the experiment had particle sizes ranging from 0.850 mm to 0.063 mm, which falls within the specification standard for haul road construction in both Edmonton and Fort McMurray (AASHTO, 1993). Hence, the collected soil could be used to construct a mine haul road similar to one in Fort McMurray. In designing a haul road on a mine site, a mining company takes into consideration the wheel load of the haul truck and the particle size distribution of the soil before deciding what type of soil will be added to the wearing course materials (Cecala et al., 2012; Thompson and Visser, 2007).

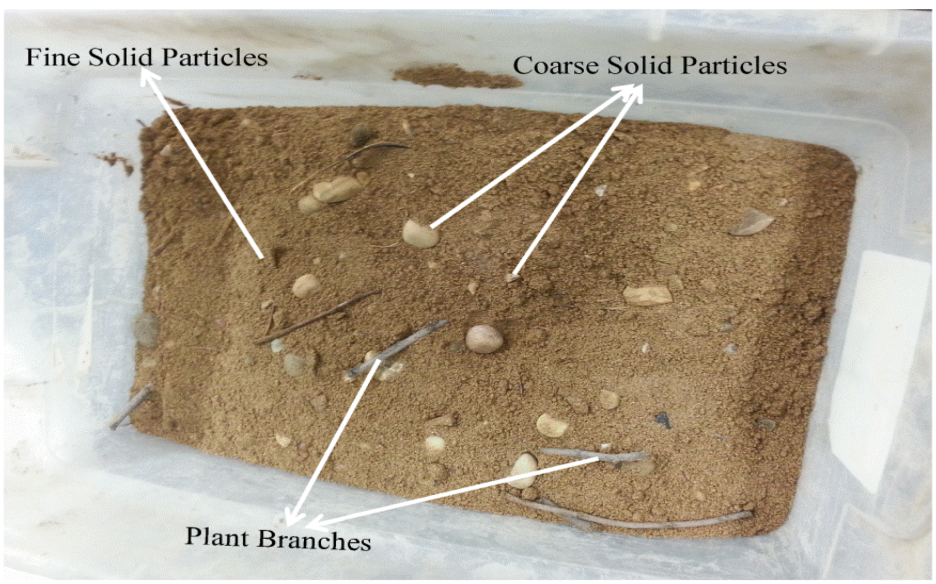

Fig 1. A photo of a fraction of the received soil sample

According to the typical design standard for the mine haul road, the particle size distribution of the used soil sample, as shown in Fig 2, falls within the design limit (AASHTO, 1993; Cecala et al., 2012), which makes the sample appropriate for a haul road design.

Fig 2 illustrates the particle size distribution of the soil sample used for the experiment. D_{10}, D_{30}, and D_{60} represent the diameter of the soil particles corresponding to the total percentage of a sample of 10%, 30%, and 60%, respectively, on the plotted particle size distribution curve. The coefficient of curvature (C_C) and the coefficient of uniformity (C_U) are calculated from D_{10}, D_{30}, and D_{60} (ASTM, 2011).

According to ASTM D2487-11 (ASTM, 2011), the coefficient curvature and coefficient of uniformity are calculated using Equations 1 and 2 to determine the classification category of the soil (ASTM, 2011).

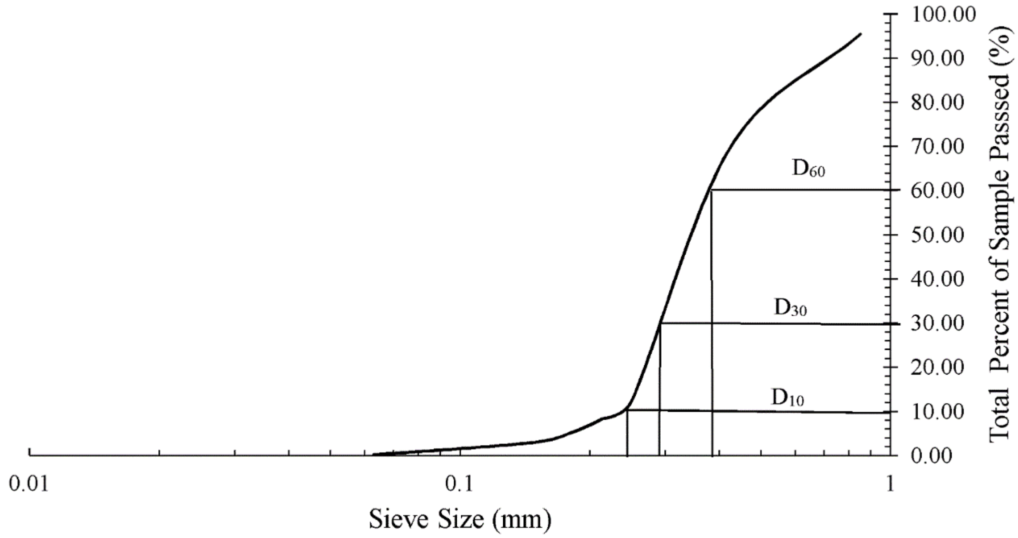

Fig 2. Particle size distribution of the soil sample

$$C_C = \frac{(D_{30})^2}{(D_{10} * D_{60})} \tag{1}$$

$$C_U = \frac{D_{60}}{D_{10}} \tag{2}$$

According to Fig 2, the CC and CU are 0.86 and 1.56, respectively. The result shows CU < 6 and CC < 1 with more than 50% of the soil sample retained on the sieve mesh with an opening of 75 µm. According to ASTM D2487-11, with these parameters, the soil sample is classified as a poorly graded sand with silt which falls within the mine haul roads design guidelines (ASTM, 2011; Tannant and Regensburg, 2001). The grading distribution of the collected soil sample for the research conforms to the typical surface layer particle size distribution for a mine haul road, which ranges from 25 mm to 0.074 mm (Tannant and Regensburg, 2001).

2.2. Dust Suppressants

Water and four different selected chemical suppressants were examined as dust suppression agents for the study. These suppressants fall into the general categories of a salt, chloride-free agent, polymer, and molasses. Fig 3 shows the different dust suppressants tested during the experiment.

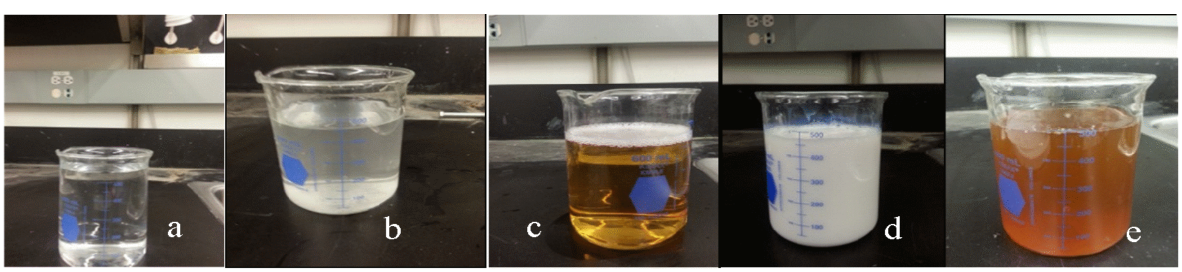

Fig 3. Dust suppression agents tested for the study: (a) Water, (b) Salt solution, (c) Chloride-free solution, (d) Polymer solution, (e) Molasses solution

Fig 3(a) shows water used as the control sample. The water used for this test is from the City of Edmonton (Canada) supplied by EPCOR Canada. The water was composed of a total chlorine level of 1.96 mg/L, total hardness of 181 mg/L as $CaCO_3$, and a total organic carbon content of 1.9 mg/L (EPCOR, 2016). Also, a composition of sodium concentration of 16.0 mg/L, a pH value of 7.7, and 0.70 mg/L of fluoride was dissolved in the water with no bacteriological data (EPCOR, 2016). Fig 3(b) shows the salt solution, which is an iodized table salt with a content composition of 570 mg and an iodide that is 70% soluble in water with a specific gravity of 2.16. Fig 3(c) shows the chloride-free solution as a non-flammable yellowish liquid with a mild odour. This chloride-free agent has a specific gravity of 1.3 and a boiling and freezing point of 100^{o}C and 0^{o}C, respectively. The pH value is in the 8-9 range. Fig 3(d) shows the polymer solution as a non-flammable white liquid with a mild odour, with a boiling and freezing point of 100 ^{o}C and 0 ^{o}C, respectively. This polymer-agent has a pH value of 8-9 and a specific gravity of 1.0. Fig 3(e) shows the molasses solution consisting of natural molasses, pure vegetable glycerin, and a pure food-grade citric acid with no additives. In addition, the molasses solution contains preservatives with 11g of sugar, 14g of total carbohydrate, and 1g of protein per 350 g of pure molasses.

2.3. Experimental Parameters

Different parameters were used for this investigation. The parameters are described in Table 1.

Table 1. Parameters and their descriptions used for the experimental work

Parameters	Description
D_{10}, D_{30}, & D_{60}	Diameter of soil sample at 10%, 30%, and 60% on particle size distribution curve
C_C & C_U	Co-efficient Curvature and Coefficient of Uniformity of the soil sample
ω_C	Weight of the container (g)
ω_D	Weight of the dried soil sample and container (g)
ω_m	Weight of the moist soil sample and container (g)
v	Volumetric dilution for surfactants (%)
ω_p	Weight of the plate (g)
ω_1	Weight of the sample before blowing (g)
ω_2	Weight of the sample after blowing (g)
$\Delta\omega$	Weight of the sample loss (g)
r	Dust retention efficiency (%)
R	Average dust retention efficiency (%)
M_S	Moisture content of the soil sample (%)

The sample of the soil was placed in an oven at a temperature of 110 ^{o}C for 120 hours to dry out all the moisture content as per ASTM standard. The temperature selection and method of calculation for drying out the moisture content in the soil sample $\left(M_S\right)$ in Equation 3 are according to the ASTM D2216-10 standard [31].

$$M_S = \frac{\omega_m(g) - \omega_D(g)}{\omega_D(g) - \omega_C(g)} * 100 \tag{3}$$

The particle size distribution of the soil sample was investigated using sieve analysis. A sieve mesh with openings ranging from 0.850 mm to 0.063 mm was used.

The selected experimental weather temperatures were based on the average quarterly statistical temperature data for the City of Edmonton between 2011 and 2016 and were provided by Environment and Climate Canada. These temperatures were similar to those in the City of Fort McMurray (ECCC, 2016). To mimic different weather temperatures, an average controlled temperature was selected for the hot, cold, and normal seasons. A wind speed of 65 km/h was set as the base velocity for the experiment to help determine how efficiently the dust suppression agents could control fugitive dust under extreme wind conditions. This speed was the highest quarterly wind speed in Fort McMurray during 2011-2016 according to Environment and Climate Change Canada.

2.4. Experimental Methodology

A general experimental procedure was followed for all the tested chemical dust suppressants under each considered temperature season for the experiment. Fig 4 is a schematic diagram showing the testing principle, and Fig 5 shows the actual experimental set-up. The set-up comprises an air blower, a measuring tape ruler, a steel tripod stand, and a flat plate. The soil sample was measured on the plate before a dosage of chemical suppressant was applied. Then, the sample was placed on the tripod stand before the wind effect was applied from the blower. The sample was then weighed again to determine how much weight was lost from the sample material. Before testing the four chemical dust suppressants, a series of base control tests were performed to determine the effects of wind speed and temperatures on a soil sample. No dust suppressants were used in those tests. The wind speed for the base control tests was 65 km/h, and it was applied for 10 seconds.

Then a series of dosage calibrations (i.e., 1 mL- 8 mL) was tried to determine the required amount of chemical suppressant to be applied on the soil sample to avoid under- or over-usage of the solution. After the calibration, a dosage of 6 mL was selected as the required amount to be applied to 20 g of the soil sample. Chepil (1959) found that there is a constant lift-to-drag ratio on elements of roughness between 0.16 and 5.08 cm for any fluid drag velocity (i.e., wind speed). After several trials, a depth of one cm was selected as the thickness of the soil sample on the plate. A stipulated time ranging from 30 minutes to 72 hours was selected as the test period for the soil sample, to assist in determining the efficiency of each dust suppressant at different temperatures.

Water was used in the control group. Four typical chemical surfactants were selected to form a solution of chemical suppressants to be examined for the experiment. In the test, using a sprinkler, 6 mL of water or a chemical suppressant was sprayed onto 20 g of soil sample on a plate. Then the sample was placed at a controlled temperature for a specified duration (i.e., 30 minutes, one hour, two hours, three hours, five hours, 24 hours, 48 hours, and 72 hours).

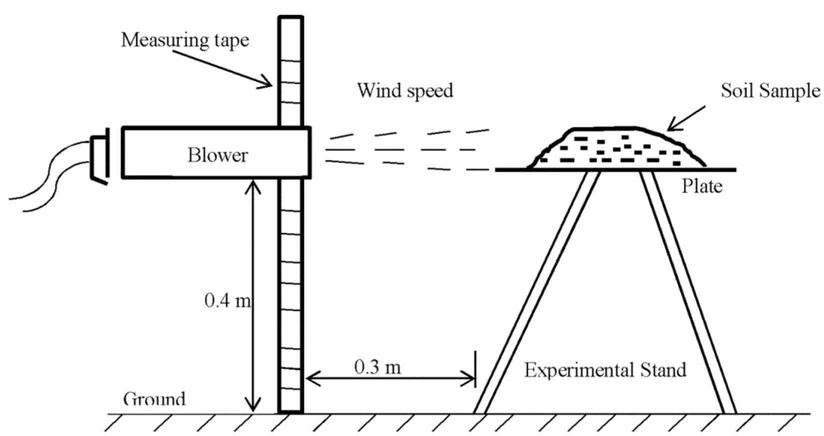

Fig 4. A representation of the experimental procedure

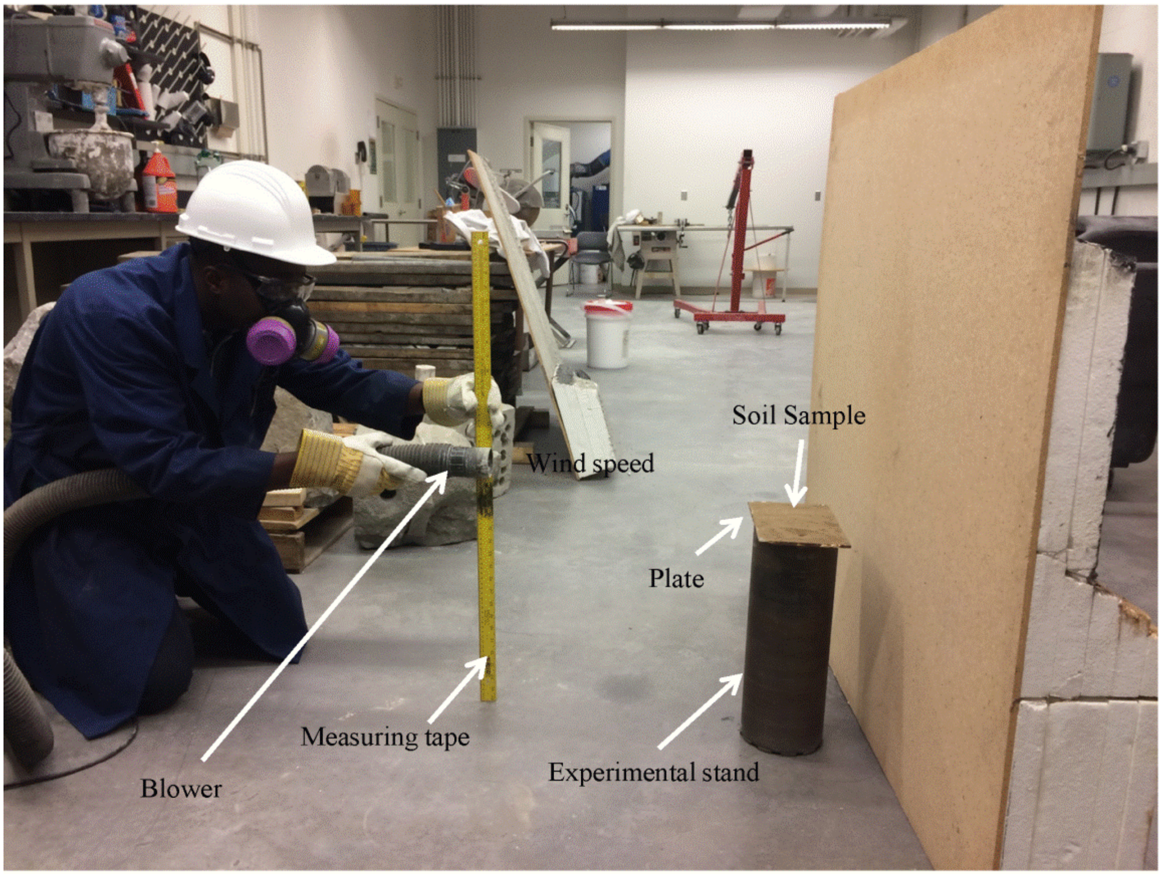

Fig 5. Experimental set-up in the laboratory

After reaching the required time for the sample to be in the oven, the sample was weighed on a scale as ω_1 (g). A wind speed of 65 km/h was applied to the sample for 10 seconds because this duration was used for the base control test. The soil sample was weighed again as ω_2 (g). The weight loss $(\Delta\omega)$ of the soil sample was determined by the difference between the two measured weights. Each test was repeated three times to improve accuracy. The weight loss helps ascertain the mass of sample loss of the material; this serves as a contributing factor when calculating the sample's dust retention efficiency.

2.5. Calculation Method

Equation 4 calculates the weight loss of the sample material ($\Delta\omega$) before and after the application of a wind speed of 65 km/h:

$$\Delta\omega(g) = \omega_1(g) - \omega_2(g) \tag{4}$$

The weight loss contributes to the calculation of the sample's dust retention efficiency. Equation 5 calculates the dust retention efficiency (r) of a chemical dust suppressant:

$$r(\%) = 1 - \frac{\Delta\omega}{(\omega_1 - \omega_p)} \tag{5}$$

Three series of dust retention efficiency were conducted for each sample, and the average of the series was taken. Equation 6 calculates the average dust retention efficiency (R) of the soil sample for the series:

$$R(\%) = \frac{r_1 + r_2 + r_3}{3} \tag{6}$$

Where r_1, r_2 and r_3 are the dust retention efficiencies for each of the sets of the soil sample.

3. Results and Discussion

3.1. Effect of the volumetric dilution concentration on dust retention efficiency

Table 2 shows the statistical result of each chemical surfactant under different volumetric dilution concentrations in water under room temperature in the laboratory. Three series of data were collected for each dilution concentration. The tested volumetric concentration of the dilution of salt ranged was 1.5%, 1.6%, 1.7%, 1.8%, and 2.0%.

Table 2. Dust retention efficiencies versus volumetric concentrations under normal temperature

Solution type	Average volumetric concentration (%)	Average dust retention efficiency (%)
Salt	1.5%	97.12% ± 0.51%
Salt	1.6%	98.25% ± 0.05%
Salt	1.7%	99.54% ± 0.10%
Salt	1.8%	99.54% ± 0.67%
Salt	2.0%	99.55% ± 0.18%
Chloride-free agent	2.0%	97.12% ± 2.48%
Chloride-free agent	3.0%	97.21% ± 2.01%
Chloride-free agent	5.0%	99.22% ± 0.82%
Chloride-free agent	8.0%	99.22% ± 0.47%
Chloride-free agent	10.0%	99.22% ± 0.57%
Polymer	2%	99.04% ± 0.52%
Polymer	3%	99.33% ± 0.70%
Polymer	5%	99.69% ± 0.04%
Polymer	8%	99.69% ± 0.11%
Polymer	10%	99.70% ± 0.08%
Molasses	2%	99.73% ± 0.02%
Molasses	3%	99.85% ± 0.09%
Molasses	5%	99.95% ± 0.02%
Molasses	8%	99.95% ± 0.03%
Molasses	10%	99.95% ± 0.03%

Table 2 also shows different dosages of volumetric concentrations of salt as a chemical surfactant in water. Salt as a chemical surfactant showed a retention efficiency of 97.12% at a dosage of 1.5%. However, the retention efficiency started to increase with time when more concentrated amounts of salt were added to the dosage. A retention efficiency of 99.54% was achieved with a 1.7% dosage and remained constant up until 2.0%. The constantly increasing trend shows that salt performs more effectively over time until the optimum dosage is achieved. A dosage of 1.7% was observed as an optimum volumetric concentration of dilution for the salt solution because beyond this dosage adding a diluted concentration had no impact on the solution's retention efficiency. At a 1.7% optimum value, high-efficiency retention was achieved with less salt. The tested dosage for the chloride-free agent, polymer, and molasses was 2%, 3%, 5%, 8%, and 10%. The volumetric concentration of the chloride-free agent, polymer, and molasses as chemical surfactants in water is shown in Table 2. Retention efficiencies of 97.14%, 99.04%, and 99.73% were achieved at a dosage of 2% for the chloride-free agent, polymer, and molasses, respectively. However, the retention efficiencies started to increase with time when more dosages of concentration were added. Retention efficiencies of 99.22%, 99.69%, and 99.95% were achieved at 5% dilution concentration for the chloride-free agent, polymer, and molasses, respectively. Each retention efficiency remained constant from the 5% dosage to the 10%. The constantly increasing trend shows that the chloride-free agent, polymer, and molasses perform better with time until the optimum dosage is achieved. A volumetric concentration of 5% was observed to be the appropriate dosage for the chloride-free solution, polymer, and molasses solution because after this concentration no added dosage affected the retention efficiency.

Researchers including Samaha and Nagger (1988) and Hancock et al. (1997) also tested different volumetric dilution concentrations until they found the optimum dilution concentration. For example, Samaha and Nagger (1988) used a liquid-by-liquid interaction between chemical surfactants and water to achieve the optimum concentration of a solution. After attaining the optimum dosage, the surface tension of the solution became constant even when they added more surfactant. Samaha and Nagger's objective was to control the concentration of chemical surfactants dispersed in water to avoid overusing of material. The results of Table 2 show the importance of dosage concentration in mixing a solution of chemical suppressant.

3.2. The performance of water under different temperatures

When no dust suppressant was applied to the soil sample, the entire sample was blown away at a wind speed of 65 km/h after 10 seconds. The soil sample that had no dust suppressant applied on it had a retention efficiency of 0% at a wind speed of 65 km/h from 30 minutes to 72 hours at different temperatures.

Fig 6 shows the impact of cold temperatures on water: there is a crusty formation of ice on the surface of the soil sample. This explains why, in the Arctic, brine needs to be sprayed on haul roads to combat freezing (BIMC, 2014; Mikkelsen, 1998; Mitchell et al., 2004; Stotterud and Magne Reitan, 1993). For example, brine was used in combating icy roads in Norway, Denmark, Canada, and the United States to increase vehicle efficiency and reduce road maintenance (BIMC, 2014; Mikkelsen, 1998; Mitchell et al., 2004; Stotterud and Magne Reitan, 1993). Fig 6 shows water at cold temperature forms a crusty slippery surface on the soil sample, which prevents the soil particles from escaping into the atmosphere to form fugitive dust. However, slippery road surfaces can lead to vehicular accidents and an extension in vehicular travel time (Mitchell et al., 2004).

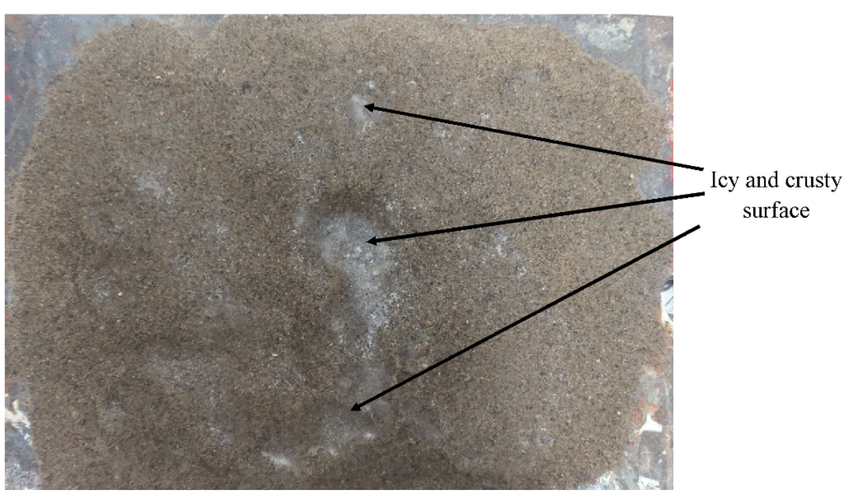

Fig 6. Icy crusty surface formed on the sample with water as a dust suppressant at cold temperatures

Fig 7(a) displays the performance of water as a dust suppressant at different temperatures (i.e., hot, cold, and normal temperatures) for a duration of 30 minutes to 72 hours. Tests were run for 30 minutes, one hour, two hours, three hours, five hours, 24 hours, 48 hours, and 72 hours to help determine the role that time plays in the potency of dust suppression at different temperatures. The corresponding dust retention efficiency associated with each time duration was recorded and plotted.

Fig 7(a) presents the retention efficiencies of water varying with time at hot, cold, and normal temperatures. Water as a dust suppressant in the hot season showed a retention efficiency of 82.02% during the first two hours. However, the retention efficiency started to decrease with time, with a retention efficiency of less than 50% at the end of the 72 hours. The reduction trend shows that water performs less effectively over time as a dust suppression agent in the hot season. Using water at normal room temperatures as a dust suppressant works effectively on dust retention at the preliminary stages, but efficiency decreases as time passes. Other researchers, including Thompson and Visser (2007), also found that water is deficient in this regard; they discovered that instead of cohering to one another, the molecules in the water spread out over time, leading to a higher surface tension. Consequently, there is greater evaporation rate, causing water to be less effective as a suppressant at hot and normal temperatures. However, at cold temperatures, dust retention efficiency is high and consistent with time.

3.3. Comparison of dust suppressants under different temperatures

Fig 7(b), (c), (d), and (e) show the average dust retention efficiencies for the chemical suppressants—salt, chloride-free, polymer, and molasses solutions—tested for 30 minutes to 72 hours under all temperature ranges.

Fig 7(b) shows the dust retention efficiency of the salt solution with time under all temperature ranges. Each point marked on the chart represents the retention efficiency of dust on the tested soil sample at different temperatures. In hot temperatures, the salt solution acted effectively when it was first applied as a dust suppressant on the soil sample. Five hours after being applied, it had achieved a retention efficiency of 94.31%. This dust retention decreased steadily up until the third day (after 72 hours) when its effectiveness reached 85.85%. The reduction trend shows that the salt solution performs less effectively over time in hot temperatures. At normal temperatures, for the first five hours, the salt solution held the soil sample together from the moment it was applied, by preventing the fugitive dust from escaping into the atmosphere. The dust retention achieved an efficiency of 95.11%. The longer the suppression agents were exposed to normal temperatures, the less efficient the solution was at dust retention; efficiencies decreased to 87.21% after 72 hours of exposure. However, in cold temperatures, the dust retention was consistent: it was 99.81% after 30 minutes of exposure and 99.93% after 72 hours. Note that mines in Canada's northern territories apply brine to control haul road dust. For example, the Mary River Iron Project in Nunavut uses brine as the sole chemical suppressant for dust control on all their project roads (BIMC, 2014). The efficacy of salt in a solution of water as a dust suppressant was also found in other literature showing that the addition of salt introduces cohesiveness between the water molecules (Cecala et al., 2012). Higher cohesiveness within a solution contributes to the solution's ability to resist atmospheric temperature and lower the evaporation rate (Thompson and Visser, 2007). The result showed in Fig 7(b) supports the claim by the study of former researcher's such as NIOSH, on the efficacy of salt solution as a dust control agent.

Fig 7(c) illustrates the how the chloride-free solution acts as a dust suppression agent on the soil sample at different temperatures. It shows the dust retention efficiency of the chloride-free solution experiment per duration for each temperature. The solution under a hot temperature showed a retention efficiency of 99.30% during the first 30 minutes of exposure. However, the retention efficiency started to decrease with time to 90.15% after 72 hours. The reduction trend shows that the chloride-free solution performed less effectively over time in a hot temperature. At a normal temperature, at the initial stage of application, the chloride-free solution worked effectively on dust retention but became less effective over time. Fig 7(c) shows how effectively the chloride-free solution works, by binding together all the particles in the soil to avoid the generation of dust. The chloride-free solution has a high dust retention efficiency compared to the water and salt solution at different temperatures.

Fig 7(d) presents the effect of the polymer solution as a dust suppressant at all temperature ranges. After 30 minutes in the hot temperature, a retention efficiency of 99.83 % was achieved, but it decreased to 99.78% after 72 hours. Although there is a reduction, the result shows the efficacy of the polymer solution at a hot temperature. At normal and cold temperatures, the polymer solution shows consistently high (above 99.87%) dust retention efficiencies. Other researchers, such as Watson et al. (2000), have reported similar findings, that the adhesiveness between the molecular structure of the polymer solution is higher, with a smaller surface tension contributing to its lower evaporation rate. Polymer emulsion is a popular chemical suppressant for road haul dust control (Goma and Mwale, 2016; Thompson and Visser, 2007) in humid subtropical climates, such as Zambia and South Africa. Among the mines that use this method is The Highveld Coalfields Mine in South Africa's Mpumalanga Province (Thompson and Visser, 2007). Fig 7(d) shows that the polymer solution is more efficient than water, the salt solution, and the chloride-free solution at controlling dust on the soil sample at different temperatures.

Fig 7(e) shows the outcome of dust retention efficiency with time when a solution of molasses is used as a dust suppression agent to control fugitive dust emissions on a soil sample at different temperatures. At a hot temperature, after 30 minutes of exposure to the molasses solution, a dust retention efficiency of 99.93% is achieved. By the end of 72 hours, the retention efficiency had increased to 99.98%. The increasing trend shows that the molasses solution is highly effective over time in the hot temperatures. At normal room and cold temperatures, the molasses solution became even more effective as time passed. Thompson and Visser (2007), Watson et al. (2000), and NIOSH (Cecala et al., 2012) also found that molasses is effective at suppressing dust: the adhesiveness between the molecular structure of the molasses solution are closer together than most chemical dust suppressants, thus contributing to smaller surface tension and less evaporation rate. However, the molasses solution is efficient regardless of the temperature. This explains why some cities located in tropical, semi-arid climates use molasses as a chemical suppressant to control dust on haul roads. For example, the city of Maharashtra in India used molasses as a dust control method on their roads after an experimental research, which proved molasses to be an effective chemical dust suppressant. Fig 7(e) shows the effectiveness of molasses as a chemical suppressant at different temperatures compared to water, and to salt, chloride-free, and polymer solutions.

3.4. Comparison of dust suppressants at a hot temperature

Fig 7(f) shows the effectiveness of all the tested dust suppressants at a hot temperature. Water was the first dust suppressant examined under a hot temperature. At the initial stage of application, water was highly efficient, but as time progressed the dust retention decreased. As the water was exposed to heat, it quickly evaporated.

Higher surface tension lowers the ability of the solution to hold particulates together (Kavouras et al., 2009). These characteristics of water make it less effective, hence the need to introduce chemicals as dust suppression agents. Fig 7(f) shows that adding chemical suppressants improves dust retention efficiency over time. The salt solution made the water a more effective suppressant, and the chloride-free solution also enhanced the efficiency.

3.5. Comparison of dust suppressants under a normal temperature

Fig 7(g) shows the effect of all the tested dust suppressants over time at room temperature. Of all the tested dust suppressants, water was the least efficient at dust retention over time: the other chemical suppressants tested were better able than water to control the dust.

Many authors (Amponsah-Dacosta, 1997; DeLuca et al., 2012; Foley et al., 1996; Gillies et al., 1999) (Jones, 1996; Kavouras et al., 2009; Plush et al., 2011; Reed and Organiscak, 2008) found that water was less effective than chemical suppressants at controlling dust. They all concluded that water is composed of molecules that are widely spaced from each other, causing a higher evaporation rate when applied as a dust suppressant. In addition, they explained that introducing a chemical suppressant in place of water works effectively because it solves the deficiency of water. Moreover, the closer the distance between molecules in a solution, the lower the surface tension of the solution, leading to a decreased in evaporation rate of the solution when applied as a dust suppressant (Jones, 1996; Plush et al., 2011; Reed and Organiscak, 2008). Fig 7(g) shows the effectiveness of the chemical suppressants compared to water at a normal temperature, consistent with findings from previous research.

3.6. Comparison of dust suppressants in a cold temperature

Fig 7(h) shows the effect of all the selected dust suppressants in cold temperatures over time. As a dust suppressant in cold temperatures, water presented a dust retention efficiency of 99.81% after 30 minutes and increased to 99.92% at the end of 72 hours. This incremental trend shows that over time, water performs more effectively a dust suppressant in cold temperatures. In cold temperature, an icy structure is formed on the soil sample when water is applied with time as shown in Fig 6, which prevents the escape of the soil particles into the atmosphere. This decreases the surface tension of water and reduces the rate of evaporation. The outcome of this result with water as the dust suppressant at cold temperature refutes the claim by former researchers, such as Thompson and Visser (2007) and Reed and Organiscak (2008), showing that the efficiency of water decreases with time.

All the selected chemical suppressants (i.e., salt, chloride-free, polymer, and molasses solutions) showed dust retention efficiencies of 99.81%, 99.83%, 99.88%, and 99.98%, respectively, after 30 minutes of exposure to cold temperatures and efficiencies of 99.93%, 99.93%, 99.94%, and 99.99%, respectively, after 72 hours. The incremental trend is evidence that the chemical suppressants are effective in the cold. This explains why most mining and road construction companies use chemical suppressants instead of water to control dust on haul roads (Amponsah-Dacosta, 1997; Cowherd et al., 1988). For example, Gilles et al. (1999) used different chemical suppressants for dust control on unpaved public roads in Merced County, California. Amponsah-Dacosta (1997) used chemical suppressants such as calcium chloride and polymerized bitumen to control dust on most surface mine haul roads in South Africa.

Fig 7(h) confirms previous research claims (Jones, 1996; Plush et al., 2011; Reed and Organiscak, 2008). At a cold temperature, it was observed that a crusty icy surface formed on the soil sample after water and the chloride-free and polymer solutions were applied over time.

3.7. Comparison of dust suppressants under all temperatures

A summary of the effect of all the tested dust suppressants at hot, cold, and normal temperatures over time is shown in Table 3. The data shows the importance of temperature on the effectiveness of chemical suppressants over time on fugitive dust.

The best solutions for dust control are those that can withstand external environmental factors such as extreme temperatures and wind speed, contributing to a good retention of moisture content on the surface of application. The ability to withstand external environmental factors makes chemical suppressants more effective than water, which requires constant reapplication to be efficient at dust control in hot and normal temperatures

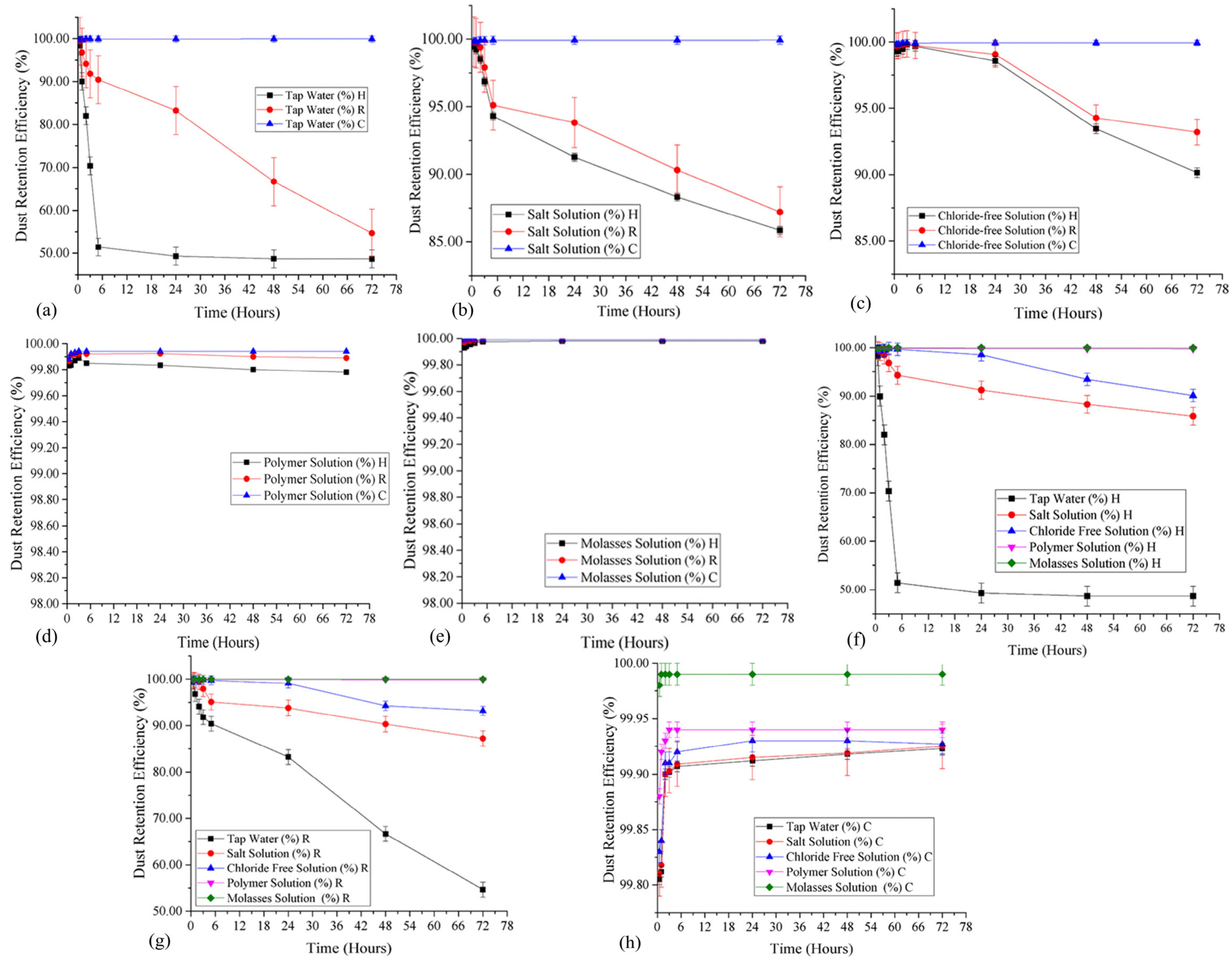

Fig 7. (a) Effect of water as a dust suppressant for all temperature ranges; (b) Effect of salt solution as a dust suppressant under all temperature ranges; (c) Effect of chloride-free solution as a dust suppressant under all temperature ranges; (d) Effect of polymer solution as a dust suppression agent under all temperature ranges; (e) Effect of molasses solution as a dust suppression agent under all temperature ranges; (f) Effect of all the tested dust suppressants at a hot temperature; (g) Effect of all the tested dust suppressants at a normal temperature; (h) Effect of all the tested dust suppressants in the cold season

Table 3. Summary of retention efficiency of all the tested dust suppressants under hot, cold, and normal room temperatures

Time (hrs)	Tap Water (%) H	Tap Water (%) R	Tap Water (%) C	Salt Solution (%) H	Salt Solution (%) R	Salt Solution (%) C	Chloride Free Solution (%) H	Chloride Free Solution (%) R	Chloride Free Solution (%) C	Polymer Solution (%) H	Polymer Solution (%) R	Polymer Solution (%) C	Molasses Solution (%) H	Molasses Solution (%) R	Molasses Solution (%) C
0.5	98.38%± 2.06%	99.40% ± 5.6%	99.81% ± 0.02%	99.45% ± 1.05%	99.80% ± 1.85%	99.81% ± 0.02%	99.30% ± 0.36%	99.70% ± 0.98%	99.83% ± 0.01%	99.83% ± 0.01%	99.87% ± 0.02%	99.88% ± 0.03%	99.93% ± 0.01%	99.97% ± 0.02%	99.98% ± 0.01%
1	90.00% ± 2.04%	96.80% ± 5.2%	99.81% ± 0.01%	99.23% ± 1.10%	99.70% ± 1.65%	99.82% ± 0.01%	99.33% ± 0.32%	99.72% ± 0.95%	99.84% ± 0.02%	99.84% ± 0.02%	99.91% ± 0.01%	99.92% ± 0.01%	99.94% ± 0.01%	99.98% ± 0.01%	99.99% ± 0.02%
2	82.02% ± 2.05%	94.11% ± 5.3%	99.90% ± 0.01%	98.53% ± 1.00%	99.40% ± 1.80%	99.90% ± 0.02%	99.47% ± 0.37%	99.82% ± 1.00%	99.91% ± 0.02%	99.87% ± 0.01%	99.92% ± 0.01%	99.93% ± 0.01%	99.95% ± 0.02%	99.98% ± 0.01%	99.99% ± 0.02%
3	70.36% ± 2.03%	91.81% ± 5.7%	99.90% ± 0.02%	96.87% ± 1.21%	97.91% ± 1.76%	99.90% ± 0.02%	99.82% ± 0.31%	99.85% ± 0.93%	99.91% ± 0.02%	99.89% ± 0.01%	99.92% ± 0.01%	99.94% ± 0.02%	99.97% ± 0.01%	99.98% ± 0.01%	99.99% ± 0.01%
5	51.42% ± 2.05%	90.42% ± 5.1%	99.91% ± 0.03%	94.31% ± 0.97%	95.11% ± 1.78%	99.91% ± 0.01%	99.68% ± 0.32%	99.73% ± 0.96%	99.92% ± 0.01%	99.85% ± 0.02%	99.92% ± 0.02%	99.94% ± 0.01%	99.97% ± 0.02%	99.99% ± 0.02%	99.99% ± 0.01%
24	49.30% ± 2.04%	83.23% ± 5.7%	99.91% ± 0.02%	91.27% ± 1.08%	93.82% ± 1.86%	99.92% ± 0.03%	98.57% ± 0.29%	99.07% ± 0.90%	99.93% ± 0.03%	99.83% ± 0.02%	99.92% ± 0.03%	99.94% ± 0.02%	99.98% ± 0.01%	99.99% ± 0.02%	99.99% ± 0.02%
48	48.68% ± 2.03%	66.68% ± 5.4%	99.92% ± 0.02%	88.32% ± 1.04%	90.32% ± 1.90%	99.92% ± 0.02%	93.45% ± 0.41%	94.27% ± 0.89%	99.93% ± 0.01%	99.80% ± 0.01%	99.90% ± 0.03%	99.94% ± 0.03%	99.98% ± 0.01%	99.99% ± 0.01%	99.99% ± 0.01%
72	48.67% ± 2.05%	54.67% ± 5.0%	99.92% ± 0.04%	85.85% ± 1.11%	87.21% ± 1.82%	99.93% ± 0.03%	90.15% ± 0.42%	93.20% ± 0.99%	99.93% ± 0.02%	99.78% ± 0.01%	99.89% ± 0.01%	99.94% ± 0.02%	99.98% ± 0.01%	99.99% ± 0.02%	99.99% ± 0.01%

4. Conclusion

This paper presents the effects of different temperature conditions on suppression agents for the control of fugitive dust emissions. The conclusive findings are enumerated as follows:

- There is an optimum volumetric concentration level of chemical surfactant in a solution. This optimum concentration plays an important role in the effectiveness of a chemical dust suppressant. An increase above the optimum concentration level will have little or no impact on a chemical dust suppressant's efficiency. In short, increasing the concentration over the optimum level incurs more cost and time, which can be avoided.
- Water performs differently depending on the environmental temperatures. In experiments with cold temperatures, at the initial application of water on the soil sample after 30 minutes, a dust retention efficiency of 99.81% was achieved, which gradually increased to 99.92% after 72 hours of exposure. Under hot and normal temperatures, a dust retention efficiency of 98.38% and 99.40%, respectively, was achieved after 30 minutes of application on the soil sample but the efficiency diminished over time to 48.67% and 54.57%, respectively, after 72 hours. This problem of diminished efficiency in dust retention under the hot and normal temperatures means that water has to be constantly reapplied to the soil sample to prevent fugitive dust emissions.
- The salt solution as a dust suppressant worked effectively in controlling the emission of dust from the soil samples. After 30 minutes of applying the salt solution suppressant to the soil samples in both hot and normal temperatures, dust retention efficiencies of 99.45% and 99.80%, respectively, were achieved. These efficiencies decreased with time to 88.85% and 87.21% after 72 hours of exposure to hot and normal temperatures, respectively. In cold temperatures, a dust retention efficiency of 99.81% was achieved during the initial 30 minutes of application to the soil sample, but efficiency gradually increased to 99.93% after 72 hours of exposure. Also, salt combined with water proved to be more effective at dust retention than water alone.
- After 30 minutes of exposure to hot, normal, and cold temperatures, the dust retention efficiencies of the chloride-free solution were 99.30%, 99.70%, and 99.93%, respectively. The effectiveness of the chloride-free solution decreased with time to 90.15%, 93.20%, and 99.93%, respectively, after 72 hours of exposure to different temperatures. This outcome shows that the chloride-free solution has a better capacity than the water-and-salt solution to control the emission of fugitive dust into the atmosphere.
- After 30 minutes of exposure to hot, normal and cold temperatures, the polymer solution demonstrated dust retention efficiencies of 99.83%, 99.87%, and 99.88%, respectively. After 72 hours, there was a reduction in the efficiencies to 99.78%, 99.89%, and 99.94%, respectively. This stable performance showed that the polymer solution is an effective dust suppressant. Unlike water and the salt and chloride-free solutions, the polymer solution's retention efficiency is not affected by temperature.
- The molasses solution showed dust retention efficiencies of 99.93%, 99.97%, and 99.98% after 30 minutes of exposure to hot, normal and cold temperatures. After 72 hours of exposure, there were efficiencies of 99.98%, 99.99%, and 99.99%, respectively, showing that the molasses solution is an effective dust suppression agent compared to the other tested agents. As with the polymer solution, the molasses solution's retention efficiency is not affected by atmosphere temperature
- A crusty, slippery surface formed on the soil sample under the cold temperature when water, the chloride-free solution, and the polymer solution were applied as dust suppression agents. No crusty, slippery surface formed when the salt and molasses solutions were used at a cold temperature.

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