Mining Optimization Laboratory

Report Seven –2015/2016

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Executive Summary

This year, we have prepared a report including 13 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 Seven (2015/2016) by considering some of the main contributors.

In paper 101, ***Shiv*** presents a simulation optimization approach for uncertainty based short term planning and proactive decision making, which provides substantial economic and operational gains. An optimization tool is presented in this paper to achieve uniform desired grade and tonnage feed to processing plants, and maximum production to comply with medium to long term roduction schedule with minimal shovel movement within a simulation model. The system considered in his model is an open pit mine with truck-shovel operations. The system includes trucks, shovels, plant crushers, waste dumps, haul road network and mining faces (scheduling polygons) with different material types based on the medium to long term production schedule. ***Shiv*** also details the development of simulation and optimization models in paper 203. He presents the implementation of the framework on an iron ore mine case study for the verification through scenario analysis. The simulation optimization framework/tool uses a discrete event simulation of mine operations, which interacts with a goal programming based mine operational optimization tool (MOOT), to capture the performance and develop uncertainty based short term schedule.

Navid presents an application of cut-off grade optimization to oil sands production scheduling and waste management in paper 102. His research investigates the impact of dynamic cut-off grade on the NPV of an operation. 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. Scenarios investigated includes: no stockpiling; stockpiling and reclaiming at the end of mine life; and stockpiling with limited reclamation duration. The model generates an optimum cut-off grade policy and a uniform production schedule for ore and dyke material over the mine life. The benefit of using the stockpile with two reclamation methods was presented. Reclaiming the stockpiled material after the mining operation resulted in an increased total ore tonnage. Also, the reclamation of stockpiled material simultaneously with the mining operation increased the total ore tonnage as well as maintaining the average head grade required by the processing plant. By maintaining the average head grade, the total NPV generated in the third scenario was higher than the second scenario.

Dylan has been working towards developing a conceptual framework for managing mineralized mine waste as a future resource in paper 103. Currently, even though most natural resources are non-renewable, the majority of mineral resources are not mined until physical depletion, but rather current economic depletion resulting in valuable minerals being left behind. The main focus of this research is to: a) propose and implement a conceptual framework for a waste management system that enables reprocessing of mineralized waste directly by the processing plant; and b) propose legislative recommendations for life of mine waste management particularly for non-renewable natural resources. The framework suggest that by reprocessing the mineralized waste when metal prices fluctuate favourably and processing technology advances, less metal will be left behind resulting in sustainable mining operations.

Ahlam started her PhD research in open pit mine planning and waste management optimization. Her research will develop a multi-objective stochastic mathematical programming model considering grade uncertainty. She has done a literature review on open pit mine planning and waste management and oil sands mining (paper 104). The paper discusses heuristic, meta-heuristic and deterministic optimization approaches, as well as application of artificial intelligence and uncertainty-based approaches to mine planning and waste management. Limitations of current mine planning models have been outlined.

Mohammad and ***Shiv*** developed a framework that takes production and maintenance schedules, haul road network, truck list and allocation strategy, shovel list, operation control parameters, and other probability distribution functions as inputs through spreadsheets and produces the reports required for analyzing the system performance and comparing expansion and modification scenarios. In paper 201, they explain all the steps required to develop and implement a simulation model by automating the procedure through programming and flexible model building and concludes by presenting normalized operation versus simulation statistics and plots to show the accuracy and reliability of their simulation model.

Ali presents a truck-shovel simulation reliability analysis with embedded dispatch optimizer in paper 202. 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 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. The tool includes a thorough implementation of a dispatching logic which mimics real-world dispatching systems in allocating trucks to the neediest shovels on the shortest travel path. Moreover, a new algorithm is developed for truck allocation by MOL and was implemented in the system. Comparing the new algorithm with the common real world dispatching systems on a case-study provides a 10% improvement in the production of the operation.

Firouz has been carrying out research on block-cave production scheduling using mathematical programming (papers 301 and 305). He models the production scheduling in block-cave mining to maximize the net present value of the project using MILP and also implements MIQP as non-linear tool to minimize the difference between the objective and the target tonnage of the mining project considering the related constraints of the operations. He uses mathematical programming as a strong tool to model the operation in block cave mining with the objective function in which minimizes the deviation of extraction from drawpoints. The problem was first formulated as a quadratic programming model then the problem was converted to a linear programming with absolute values. Technical and operational constraints such as mining capacity, average grade for production, continuous mining, drawpoint's life, draw control and number of active drawpoints are considered for the operations. Testing both the quadratic and the linear model with absolute values for a real case mining project shows that the linear model with absolute values is easier and faster to solve.

In paper 302, ***Amir*** discusses the caving process and all effective parameters. Then, he introduces the interaction matrix based on the rock engineering system (RES) to study the influencing parameters in rock mass fragmentation. The interaction matrix analyzes the interrelationship between the parameters affecting rock engineering activities. The interaction matrix for influencing parameters are established and coded by ESQ (Expert Semi Quantitative) approach. As a result, the high dominant or subordinate, and also the most interactive parameters, are introduced. The proposed approach could be a simple but efficient tool in the evaluation of the parameters affecting the fragmentation of rock mass in block-cave mines and as a result, useful in decision-making under uncertainties.

Saha has been working towards development of a methodology to find the best extraction level under grade uncertainty for block-cave mining (paper 303). The main goal of the study is to develop a framework to find the best level of extraction under grade uncertainty. In this paper, several realizations are modelled by using geostatistical studies to consider the grade uncertainty. After determining the best extraction level, the production schedule is generated for the best advancement direction and in presence of some constraints at the extraction level using a mixed-integer linear model.

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. He also compares recoverable reserves between simulation and kriging for block caving in paper 304. He conclude that despite the fact that the block caving design depends on many parameters and constraints and its evaluation is very challenging, an efficient extraction layout could be obtained by using a set of realizations. Managing a huge number of realizations is still a bit time consuming, hence the usage of 40 to 100 realizations is recommended. Moreover, hardware and software have been improving over the years.

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Mining Optimization Laboratory (MOL) Researchers / Graduate Students

Following are researchers and students affiliated with Mining Optimization Laboratory in September 2016.

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 of Mining Engineering

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5.	**Mohammad Tabesh**	PhD, Research Associate – 2015/09
6.	**Shiv Prakash Upadhyay**	PhD Candidate – 2011/09
7.	**Firouz Khodayari**	PhD Student – 2014/01
8.	**Ali Moradi Afrapoli**	PhD Student – 2014/09
9.	**Saha Malaki**	MSc Student – 2014/09
10.	**Myagmarjav Batsukh**	MSc Student – 2015/09
11.	**David Omane**	MSc Student – 2015/09
12.	**Luisa Fernanda Montes**	MSc Student – 2015/01
13.	**Efrain Ugarte-Zarate**	MSc Student (CCG) – 2015/09
14.	**Regan Schafer**	MSc Student – 2015/09
15.	**Zeinab Basiri**	MSc Student – 2016/09
16.	**Amir Azadmehr**	Visiting PhD Student – 2015/09
17.	**Farshad Nezhadshahmohammad**	Visiting PhD Student – 2016/09
18.	**Navid Seyed Hosseini**	MSc Student – 2015/09
19.	**Dylan Caverson**	MEng Student – 2016/01
20.	**Ahlam Maremi**	PhD Student – 2015/09
21.	**Daniel Ankomah**	PhD Student – 2016/09

Short-term Production Planning in Open Pit Mines using Dynamic Shovel Allocations

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Abstract

The complexity and uncertainties associated with mining operations often lead to deviations from strategic plans, forcing a reactive planning approach. This paper presents a simulation optimization approach for uncertainty based short term planning and proactive decision making, which provides substantial economic and operational gains. An optimization tool is presented in this paper to achieve uniform desired grade and tonnage feed to processing plants, and maximum production to comply with medium to long term production schedule with minimal shovel movement within a simulation model. A verification of the model is presented in this paper using an iron ore mine case study.

1. Introduction

In mine planning context, long term and medium term plans are generally referred to as strategic plans, whereas short term and operational plans constitute tactical plans. Short term and operational plans are developed considering the detailed operations to ultimately comply with the medium and long term plans and also achieve operational objectives on a day-to-day basis. Detailed short term plans are desired to provide equipment planning and sequence of extraction of mining faces over short time horizons such as months or weeks. The prime objective of a short term mine plan is to provide sequential shovel placements and truck allocation such that quantitative and qualitative operational targets are met while there is a high level of compliance with strategic mine plans.

A main problem of concern in any mining operation is a short-term planning framework/tool that generates near-optimal production schedules in the presence of uncertainty that satisfies the operational objectives. These objectives are predominantly maximizing the utilization of shovels and crushers at the processing plants, and also meeting the grade blending requirements at the processing plants. This framework/tool must also comply with strategic schedules and capable of assisting in proactive short term decision making to realize strategic objectives. The proactive planning minimizes the deviations from the strategic mine plans and will assist in minimizing substantial losses in revenue that mining organizations incur every year due to opportunity loss.

Newman *et al.* (2010) provides a comprehensive review of the application of operations research in mine planning. Mine planning and scheduling has received sufficient attention of the researchers, but has remained limited to long term planning or truck dispatching. Short term mine planning and scheduling problem is addressed by very few researchers. Modeling the detailed mining operations over multiple periods incorporating all the faces, shovel movements between faces, truck allocations and plants, increases the problem size and poses the limitation on the solvability of the model as observed by L'Heureux, *et al.* (2013). Bjørndal, *et al.* (2012) observes that even state of the art hardware and software cannot handle the size and complexity of such detailed scheduling models.

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L'Heureux*, et al.* (2013) presents a detailed model for short term planning for a period of up to three months, where they consider precedence among blocks, precedence among operational activities, drilling, blasting, transportation, processing, movement of shovels, drills and more in detail as operating constraints. Gurgur*, et al.* (2011) proposed a LP model for short term planning, but do not consider mine operations in details. Fioroni *et al.* (2008) proposed a simulation optimization model to generate short term mine plans over monthly resolution. Their model does not consider any mining precedence constraints limiting it to run over shorter time horizons. Eivazy & Askari-Nasab (2012) proposed a multi-destination mixed integer linear programming model to minimize the overall operating cost to generate short term production schedules. One major limitation of the existing approaches is that grade blending objectives optimized at short term planning stage are hard to achieve at operational stage, due to mismatch between planned and operating ore faces, and realized mainly through truck dispatching logic. Another major drawback of existing models is that they fail to consider the dynamic nature of mining operations leading to frequent updates of operational plans as well as short term plans. The dynamic components of the system which must be accounted at this stage include equipment availabilities due to failures, changing rates of production from shovels based on their location, haulage capacities, and unavailability of faces due to precedence requirements. The capturing of dynamic nature of the mining systems provides an opportunity to develop more robust mine plans and thus supports an opportunistic proactive planning framework by determining the bottlenecks of the operation.

To capture the operational uncertainty, a bottom up approach is proposed in this paper, where production operations within a simulation model are optimized iteratively to develop short term production plans constrained by the strategic mine plans. The operational optimization tool here works as an upper stage of a multi-stage dispatching system proposed by Elbrond and Soumis (1987), White and Olson (1986) and Soumis, *et al.* (1989). The operational optimization tool at this stage is required to optimize the operational objectives by providing optimal shovel placements and target productions. The scope of the existing multi-stage dispatching models (Elbrond & Soumis, 1987; Li, 1990; Soumis*, et al.*, 1989; Subtil*, et al.*, 2011; Temeng*, et al.*, 1997, 1998; White & Olson, 1986) in the literature has remained limited to truck allocations for better operational results. The multi-stage model proposed by Soumis *et al.* (Soumis*, et al.*, 1989) provides shovel allocation decisions using man machine interaction, which render it unusable for a dynamic tool. In a similar approach, Lestage*, et al.* (1993) proposed a computerized tool for daily operational decision making by optimizing the system over a given time horizon.

The approach proposed in this paper is an iterative simulation optimization approach which breaks the problem into smaller number of periods and simulates the operations over longer time horizons. This approach considerably reduces the problem size and captures the operational uncertainty at the same time. This bottom-up approach addresses the solvability issue to a great extent. Using the dynamic decision making tool at the operational decision making stage, grade blending can also be achieved better by first optimally placing the shovels and then using truck dispatching.

The proposed framework/tool in this paper solves the short term mine planning problem using a simulation-optimization approach. A dynamic decision making tool, Mixed Integer Linear Goal Programming (MILGP) model, is proposed for dynamic operational decision making within a simulation model of the mining operations to generate short term plans capturing the operational uncertainty with a reduced run time. The dynamic tool provides shovel allocation and target productions for the current state of the system by optimizing the operations for a predetermined number of periods of time in future. The MILGP model provides shovel allocation decisions based on the available mining faces in the strategic schedule, thus linking the operational decisions with the strategic plans. The MILGP model can also be used standalone for short term production planning as a traditional approach which is not considered in this paper.

The MILGP model presented here is an improvement to the previously published model (Upadhyay & Askari-Nasab, 2016), where the current model provides allocation decisions considering near future allocation requirements as well. The foresight was observed to be an essential characteristic requirement of the model, because allocations made solely on current state do not take into account future allocation requirements and thus the decisions may not be optimal on an aggregated basis for the entire planning period.

The objective of this paper is to present and test the simulation optimization approach for short term mine production planning and scheduling, with a focus on the MILGP optimization model. To illustrate the proposed model, the paper is structured as follows: the objectives, definitions and scope and limitations of the model are presented in problem definition section. The proposed MILGP model is then described detailing the objectives and constraints of the mining operation. A case study is then presented and the implementation results are discussed. Finally, the conclusion and future scope of the research are presented.

2. Problem definition

2.1. System

The system considered in this model is an open pit mine with truck-shovel operations. The system includes trucks, shovels, plant crushers, waste dumps, haul road network and mining faces (scheduling polygons) with different material types based on the medium to long term production schedule.

2.2. Objective

The objective of the MILGP model is to provide near optimal shovel allocations and target productions at a system state to achieve operational objectives of:

1. Maximum production
2. Meeting the desired feed to processing plants
3. Meeting the grade blending requirements of the processing plants
4. Minimize shovel movements

The goal of the paper is to develop, implement, and verify the simulation optimization framework for generating efficient and practical short term mine production schedule.

2.3. Definitions

2.3.1. Faces

Faces in the model refers to the clusters of the blocks grouped together based on similarity in material content and rock types, also known as scheduling polygons. The basic mining unit considered in the model is a face which reduces the problem size considerably compared to small blocks as mining units. This assumption limits the model to capture the grade variability among blocks clustered together, which can be minimized while developing clusters. Other block aggregation techniques may also be used to generate bigger blocks as mining units. As blasting and excavation operations are carried out over wider areas consisting of a group of blocks, this assumption of considering clusters as basic mining unit is practically more representative of the mining operations comparing to the blocks level.

2.3.2. Decision and optimization time frames

For optimal short term production scheduling, following a simulation optimization approach, it is considered essential for the model to make decisions for the current state considering future decision requirements at the same time. The time frame for which the decision is required in the simulation model is called the decision time frame in this paper, which is the first period. The optimization time frame includes the total time for all the periods (Fig. 1). So if simulation is desired to have decisions for a shift of 12 hours (1 shift per day) with 30 periods, the decision time frame is a shift of 12 hours and optimization time is a month, i.e. allocation decisions will be provided to the simulation model for one shift, but the model optimizes the operations for an entire month. This helps the simulation optimization approach to foresee the unavailability of faces and provide shovel allocations to minimize face unavailability.

Optimization Time Frame					
Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Decision Time Frame (T)					

Fig. 1. Decision and optimization time frame of the model

2.4. Scope and limitations

The MILGP model is a dynamic decision making tool for shovel allocation optimization.

- It can be used stand alone to generate short term production schedules.
- It can be used in combination with a deterministic mine discrete event simulation model for a deterministic short-term production schedule.
- It can be used in conjunction with a stochastic discrete event simulation model for scenario analysis and developing uncertainty based short term production schedules and opportunistic proactive planning.
- The model is developed as part of a multi-stage dispatching system and it can be implemented in conjunction with a real-time dispatching system in an operating mine for operational decision making.

The combined simulation optimization model is used in this paper to generate deterministic short-term production schedule.

The model although considers the most critical operational objectives and constraints for shovel allocations, there are always other considerations in place which are taken into account for shovel allocations by the planners at site. The problem, as can be perceived, requires human intervention to account for some other considerations such as haul road development or drilling, blasting and face development activities in specific parts of the pit. Thus the implementation of the model as part of a multi-stage dispatching for real time decision making may not be possible in its current form. As the main goal of this model is to work in conjunction with a simulation model for operational planning purposes, the extent of modeling is reasonable for practical short term mine scheduling.

3. MILGP model formulation

The mixed integer linear goal programming (MILGP) model is a shovel-truck allocation optimization model. The objective of this model is to provide shovel allocations and target productions; and to concurrently maximize the production, optimize ore tonnage received at processing plants and minimize the deviations in grade requirements at various ore destinations. To achieve these objectives, a non preemptive goal programming approach is adopted for the model. The constraints and the formulation of the objective function are described in this section (see Appendix for details on the indices, variables and parameters used in this model).

3.1. Variables

The constraints have been formulated to account for shovel assignments using a binary variable $a_{s,f,p}$ which becomes true if shovel 's' is assigned to face 'f' in period 'p' . To control the number of binary variables, shovel movements are also controlled using the same assignment variables in conjunction with another binary variable $m_{f,p}$ to keep track of mined out faces. Another binary variable $y_{s,p}$ is used, for an if-else constraint, to model the continuous nature of shovel movements. Integer variable $n_{t,f,d}$ is used to formulate number of required truck trips between faces and destinations in the decision time frame. Number of truck trips is derived only for the decision time frame, i.e. the first period of optimization, and thus $n_{t,f,d}$ variable is not indexed over 'p'. Other real value variables include: $x_{s,f,d,p}$ as fraction of tonnage at face, to model production by shovels from faces to destinations in each period, $x^{-}_{s,p}$ as fraction of capacity of shovels, to model negative deviation in production by shovels compared to their capacity, $\delta^{-}_{d^c,p}, \delta^{+}_{d^c,p}$ as fraction of target capacity of processing plants, to model negative and positive deviation in production received at processing plants compared to target, $g^{-}_{k,d^o,p}, g^{+}_{k,d^o,p}$ as negative and positive deviation in grades received at ore destinations, $l_{f,p}$ as tonnage of material available at faces in each period, $r_{s,p}$ as movement time for shovel relocations in each period and, $r^{rem}_{s,p}$ and $r^{act}_{s,p}$ as remaining movement time for shovels to be covered in next period and actual movement time for relocation in each period.

3.2. Goals

Four operational objectives have been considered here as goals:

1. Maximum production objective is formulated as minimizing the negative deviation in production by shovels compared to their maximum capacity.

$$\Psi_1 = \sum_{p}\sum_{s}\left(\frac{1}{p}\right) \times x^{-}_{s,p} \tag{1}$$

2. Objective to meet the desired tonnage feed to processing plants is formulated as minimizing the negative and positive deviation in production received at processing plants.

$$\Psi_2 = \sum_{d^c}\sum_{p}\left(\frac{1}{p}\right) \times (\delta^{-}_{d^c,p} + \delta^{+}_{d^c,p}) \tag{2}$$

3. Objective to meet grade blend requirements at processing plants is formulated as minimizing the negative and positive deviation in grades received at processing plants.

$$\Psi_3 = \sum_{p}\sum_{d^o}\sum_{k}\left(\frac{1}{p}\right) \times (g^{-}_{k,d^o,p} + g^{+}_{k,d^o,p}) \tag{3}$$

4. Shovel movement objective is formulated as minimizing the total movement time of shovels over all periods.

$$\Psi_4 = \sum_{s}\sum_{p} r_{s,p} \tag{4}$$

A weight, as inverse of period, is multiplied to the first three objectives to prioritize the first period, which is the decision time frame. As shovel movement objective requires seeing future movements, no priority is assigned to it based on period. It is desired here that shovel allocations are made such that first three objectives are achieved better for the decision time frame but shovel movements are minimized over the whole optimization time frame.

3.3. Objective function

The problem is optimized following a non-preemptive weighted sum approach as described by Grodzevich & Romanko (2006). Before optimizing the goal individual objectives are optimized to determine their respective values in pareto optimal space. Individual objectives are then normalized and combined to generate the goal given in eq. (5).

$$\Psi = W_1 \times \overline{\Psi}_1 + W_2 \times \overline{\Psi}_2 + W_3 \times \overline{\Psi}_3 + W_4 \times \overline{\Psi}_4 \tag{5}$$

3.4. Constraints

Constraints have been formulated to model a mining operation where shovels are assigned to their initial faces where they were working at the start of optimization. Shovels are not allowed to leave a face un-mined, i.e. shovels won't be reassigned to a new face unless they have mined out their current working face completely. If a shovel is re-assigned to a new face it will take some movement time to reach the new face leading to some production loss. Shovel movement time is based on the defined speed of shovel and location of the new face, following the ramp if on a different bench, or a straight line distance if on the same bench.

Constraint eq. (6) to (12) control the shovel allocation to faces in each period. As the optimization time frame of the model is divided into multiple periods, an assignment variable, indexed over multiple periods, is used for shovel assignment in each period. Constraint eq. (6) does not let multiple shovels to be assigned to any one face, which means any face can be mined by only one shovel. Eq. (7) assigns shovels in the first period to their initial faces where shovels were working at the start of optimization. Constraint eq. (8) allows any shovel to be assigned to at maximum two faces in any period. This constraint allows the shovels move to their new faces when their working face is mined out.

$$\sum_s a_{s,f,p} \le 1 \qquad \forall f \ \& \ \forall p \tag{6}$$

$$a_{s,Fi_s,p} = 1 \qquad \forall s \ \& \ p = 1 \tag{7}$$

$$\sum_f a_{s,f,p} \le 2 \qquad \forall s \ \& \ \forall p \tag{8}$$

Eq. (9) models the same constraint as eq. (8), but also controls *when* a shovel can work at two faces. Left hand side of the constraint is the maximum number of faces a shovel is assigned to in any period. The right hand side of the constraint (9) looks over all the faces and takes a very large value if shovel 's' is not assigned to the face in that period. For the faces shovel is assigned to, last part of the constraint will become zero and remaining portion may take a value of 1 or 2. If the shovel was working on the face in the previous period and still hasn't finished mining it, maximum number of faces that shovel can work on can be 1, but if the face is mined out completely, $m_{f,p}$ will become 1 and thus the shovel will be allowed to be assigned to another face. For the new face $a_{s,f,p-1}$ and $m_{f,p}$ will be zero and thus the constraint will still hold true and allow the shovel to be assigned to two faces in that period. Constraint (10) force a shovel to remain assigned to a face in the next period, if it is not mined out in that period, i.e. a shovel will continue working on a face until it is completely mined.

$$\sum_f a_{s,f,p} \le a_{s,f,p} + m_{f,p} + (1 - a_{s,f,p-1}) + (1 - a_{s,f,p}) \times BM \qquad \forall s, f, p \tag{9}$$

$$a_{s,f,p+1} \ge a_{s,f,p} - m_{f,p} \qquad \forall s, f, p = 1 \ldots P-1 \tag{10}$$

Constraint (11) ensures that shovels cannot be assigned to a face which is already mined, except if face was mined by itself and shovel is sitting idle. Constraint (12) ensures that if shovel 's' was assigned to face 'f' and to only one face in period 'p', it will continue to be assigned to face 'f' in the next period.

Constraint (12) works in conjunction with constraint (10) to eliminate any scenario where a face is mined out in a period and shovel movement cannot be finished in that period, model tries to assign the shovel to the new face in the next period without modeling the movement time and the loss in production.

$$a_{s,f,p+1} \le 1 + a_{s,f,p} - m_{f,p} \qquad \forall s, f, p = 1...P-1 \tag{11}$$

$$a_{s,f,p+1} \ge 2 \times a_{s,f,p} - \sum_{f} a_{s,f,p} \qquad \forall s, f, p = 1...P-1 \tag{12}$$

Constraints eq. (13) to eq. (18) control the travel time of shovels from one face to the next one. Eq. (13) determines the travel time of shovels in a period. As travel time variable is indexed over shovel and period only, it is not possible to formulate as equality constraint. Thus travel time is formulated as greater than or equal to the required travel time between faces. As travel time will incur loss in production, model will make travel time variable equal to the required travel time. Constraint (13) is formulated for all the faces and to determine the travel time between the assigned faces. For the face, shovel is not assigned to, last part of the constraint makes the right hand side negative and thus does not affect the value of the travel time variable. For the faces shovel is assigned to, it calculates the distance as the sum of distance from that face to all other assigned faces, which includes the same face itself and the second face. As the distance between the same face is zero, constraint (13) makes the travel time variable $r_{s,p}$ greater than or equal to the required travel time between the assigned faces.

$$r_{s,p} \ge \sum_{f^1} a_{s,f^1,p} \times \Gamma^F_{f^1,f} \Big/ S_s - (1 - a_{s,f,p}) \times BM \qquad \forall s, \forall f \ \& \ p \tag{13}$$

Constraint (14) is included to model the continuous nature of shovel movement. If a shovel starts traveling towards the end of a period, it may finish the travel in the next period. $r^{act}_{s,p}$ and $r^{rem}_{s,p}$ variables divide the required travel time into actual travel time in that period and the remaining travel time for the next period. Constraint (15) is included to make sure travel time is zero, if shovel is assigned to only one face in a period.

$$r_{s,p} = r^{act}_{s,p} + r^{rem}_{s,p} \qquad \forall s \ \& \ \forall p \tag{14}$$

$$r_{s,p} \le \left(\sum_{f} a_{s,f,p} - 1 \right) \times BM \qquad \forall s \ \& \ \forall p \tag{15}$$

Constraints (16), (17) and (18) are formulated to ensure that no production is possible from the newly assigned face in a period if shovel hasn't finished traveling in that period. Constraints (17) and (18) make sure that binary variable $y_{s,p}$ becomes true if remaining travel time is zero and false if greater than zero. Then this binary variable $y_{s,p}$ is used in constraint (16) to control production from the newly assigned face. Constraint (16) is formulated for all the faces and right hand side takes a very large value for all other faces where shovel is not working and thus do not put any constraint on the production from those faces. For the face where shovel was initially working, first part of the right hand side takes a very large value, thus do not affect the production from that face as well. For the newly assigned face, first part of the right hand side of constraint (16) becomes zero and production from the new face is controlled by the binary variable $y_{s,p}$, which ensures that if remaining travel time is greater than zero, ($y_{s,p}$=0), no production is possible from the newly assigned face in that period.

$$\sum_{d} x_{s,f,d,p} \le \left(1 - a_{s,f,p} + a_{s,f,p-1}\right) \times BM + y_{s,p} \times BM \qquad \forall s, \forall f \ \& \ \forall p \tag{16}$$

$$r^{rem}_{s,p} \ge \left(1 - y_{s,p}\right) \times \left(2 \times \varepsilon\right) \qquad \forall s \ \& \ \forall p \tag{17}$$

$$r_{s,p}^{rem} \le y_{s,p} \times \varepsilon + \left(1 - y_{s,p}\right) \times BM \qquad \forall s \,\&\, \forall p \qquad (18)$$

Constraint (19) controls the total production possible by the shovels in any period, which has to be less than the maximum production capacity of the shovels in any period. First part of the constraint (19) is the total production by the shovel from all the faces in that period and the second part is the production lost due to the travel in that period, which includes remaining travel time from the last period and the new travel time, if any, in the current period.

$$\sum_f \sum_d x_{s,f,d,p} \times O_f + \left(r_{s,p-1}^{rem} + r_{s,p}^{act}\right) \times 60 \times X_s \big/ L_s \le T \times 3600 \times X_s \times \alpha_s^S \big/ L_s \qquad \forall s \,\&\, \forall p \qquad (19)$$

Constraints (20) to (24) determine mined out faces and the material available at faces. Eq. (20) is the equality constraint to read the material available at the faces initially and eq. (21) determines the material available at the faces in the subsequent periods based on the production by shovels. Eq. (22) and (23) determines if a face is mined out completely during a period. Eq. (22) is a strict in-equality constraint and thus is modelled using a very small decimal value 'epsilon', which converts it to a general in-quality constraint in the model to be solved directly using CPLEX solver (CPLEX, 2014). Eq. (24) ensures that if a face is mined out during a period, it will remain mined out in the subsequent periods.

$$l_{f,p} = O_f \qquad \forall f \,\&\, p = 1 \qquad (20)$$

$$l_{f,p+1} = l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \qquad \forall f \,\&\, p = 1 \ldots P-1 \qquad (21)$$

$$l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \ge \left(1 - m_{f,p}\right) \times \left(O_{\min} + \varepsilon\right) \qquad \forall f \,\&\, \forall p \qquad (22)$$

$$l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \le m_{f,p} \times O_{\min} + \left(1 - m_{f,p}\right) \times BM \qquad \forall f \,\&\, \forall p \qquad (23)$$

$$m_{f,p+1} \ge m_{f,p} \qquad \forall f \,\&\, p = 1 \ldots P-1 \qquad (24)$$

Eq. (25) is an equality constraint on the production to capture the negative deviation in production by a shovel compared to its maximum capacity. Eq. (26) ensures that there is no production possible from a face by a shovel if the shovel is not assigned to that face in that period. Eq. (27) and (28) limit the total production from a face to ore or waste destinations based on the amount of material available at the face and whether it is ore or waste.

$$\sum_d \sum_f x_{s,f,d,p} \times O_f \big/ X_s^+ + x_{s,p}^- = 1 \qquad \forall s \,\&\, \forall p \qquad (25)$$

$$\sum_d x_{s,f,d,p} \le a_{s,f,p} \qquad \forall s, \forall f \,\&\, \forall p \qquad (26)$$

$$\sum_s \sum_{d^o} x_{s,f,d^o,p} \times O_f \le l_{f,p} \times Q_f \qquad \forall f \,\&\, \forall p \qquad (27)$$

$$\sum_s \sum_{d^w} x_{s,f,d^w,p} \times O_f \le l_{f,p} \times (1 - Q_f) \qquad \forall f \,\&\, \forall p \qquad (28)$$

One major requirement of the model is to provide realistic shovel allocations. Thus it is necessary to include precedence requirements within the model. To ensure that a shovel is assigned to a face only if the face is available for mining, eq. (29) is included in this model. Eq. (29) specifies that assignment variable for a face cannot take a value of one unless all the faces in its precedence set are mined out completely.

$$N_f^F \times \sum_s a_{s,f,p} - \sum_{f'} m_{f',p} \leq 0 \qquad \forall f, \forall p \,\&\, f' \in PrecedenceSet_f \tag{29}$$

The tonnage of ore delivered at the processing plants is controlled using eq. (30) to (32). Eq. (30) is a soft constraint which determines positive or negative deviation in production received at processing plants and eq. (31) and eq. (32) puts a limit on the allowed deviation from the capacity. Eq. (33) is an equality constraint which determines the positive or negative deviation in tonnage content of material types received at ore destinations which is minimized in the objective function.

$$\sum_s \sum_f x_{s,f,d^c,p} \times O_f \Big/ \left(Z_{d^c} \times T\right) + \delta^-_{d^c,p} - \delta^+_{d^c,p} = 1 \qquad \forall d^c \,\&\, \forall p \tag{30}$$

$$\delta^-_{d^c,p} \leq \Lambda^-_{d^c} \big/ Z_{d^c} \qquad \forall d^c \,\&\, \forall p \tag{31}$$

$$\delta^+_{d^c,p} \leq \Lambda^+_{d^c} \big/ Z_{d^c} \qquad \forall d^c \,\&\, \forall p \tag{32}$$

$$\sum_s \sum_f x_{s,f,d^o,p} \times O_f \times \bar{G}_{f,k} + g^-_{k,d^o,p} - g^+_{k,d^o,p} = \sum_s \sum_f x_{s,f,d^o,p} \times O_f \times G_{k,d^o} \qquad \forall k, \forall d^o \,\&\, \forall p \tag{33}$$

Constraint eq. (34) to (37) provide truck allocations to shovels. As only first period in the optimization time corresponds to decision time frame and truck allocation decisions do not significantly affect the objectives of the model (if sufficient haulage capacity is available), truck allocations are made only for the first period. Eq. (34) specifies that total number of truck trips from a face to a destination should be sufficient to transport the material produced by the shovel in the first period. Eq. (35) puts an upper limit on the total number of truck trips specifying that even if some over-loading or under-loading of trucks takes place, total tonnage haul capacity by the number of truck trips should be less than the specified deviation, which is considered as one truck load in this model. Eq. (36) controls the total number of truck trips based on the truck type. Eq. (36) specifies that if a truck type is not desired to work with a shovel, number of truck trips from the corresponding face has to be zero. Eq. (36) also specifies that number of truck trips from a face with no shovel assigned to it, has to be zero. Eq. (37) puts a limit on the possible number of truck trips based on the available time and number of trucks of each type available.

$$\sum_s x_{s,f,d,p} \times O_f \leq \sum_t n_{t,f,d} \times H_t \qquad \forall d, \forall f \,\&\, p = 1 \tag{34}$$

$$\sum_s x_{s,f,d,p} \times O_f + J \geq \sum_t n_{t,f,d} \times H_t \qquad \forall d, \forall f \,\&\, p = 1 \tag{35}$$

$$\sum_d n_{t,f,d} \times H_t \leq \sum_s \left(\sum_d x_{s,f,d,p} \times O_f + a_{s,f,p} \times J \right) \times M^t_{t,s} \qquad \forall t, \forall f \,\&\, p = 1 \tag{36}$$

$$\sum_f \sum_d n_{t,f,d} \times \bar{T}_{t,f,d} \leq T \times 60 \times N_t^T \times \alpha_t^T \qquad \forall t \tag{37}$$

To run the model in a dynamic environment in conjunction with a simulation model eq. (38) is added to model the shovel failures. Eq. (38) specifies that no production is possible by a failed shovel although it will remain assigned to its current face. Shovels are locked to material types (ore or waste) using eq. (39)

$$\sum_f \sum_d \sum_p x_{s,f,d,p} \leq \left(1 - \phi_s\right) \times BM \qquad \forall s \tag{38}$$

$$a_{s,f,p} \leq 1 - abs\left(M_s^{ore} - Q_f\right) \qquad \forall s, \forall f \,\&\, \forall p \tag{39}$$

4. Case study

A case study of an iron ore open pit mine is considered to verify the model. Based on the drillhole prospecting data, mine planning activities have been carried out and a long term production schedule is generated. Year 11 was selected as the strategic plan for the case study. The schedule requires 16.42 MT of ore and 39.11 MT of waste to be mined in year 11 with four benches 1745, 1730, 1610 and 1595. A clustering algorithm (Tabesh & Askari-Nasab, 2013) is run to cluster similar blocks together to generate 174 mining faces (polygons) out of 4227 blocks to be mined in year 11 with four benches. Fig. 2 presents the clustered mining blocks as faces on the bottom bench 1595 scheduled in year 11.

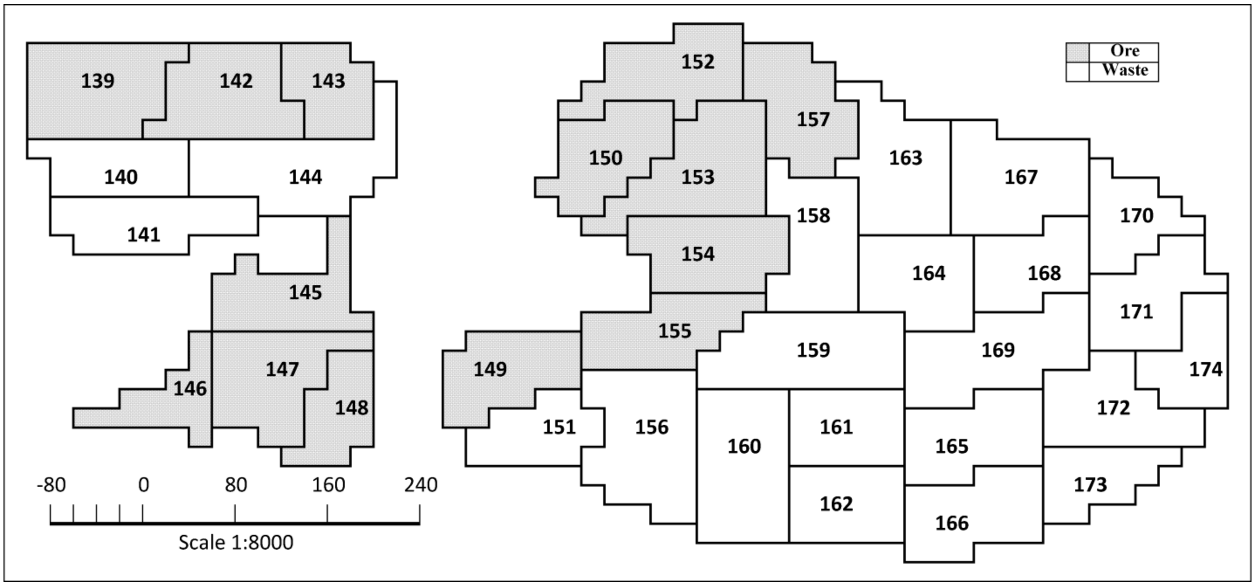

Fig. 2. Clustered mining blocks as faces (numbered) in the bench 1595 scheduled in Year 11

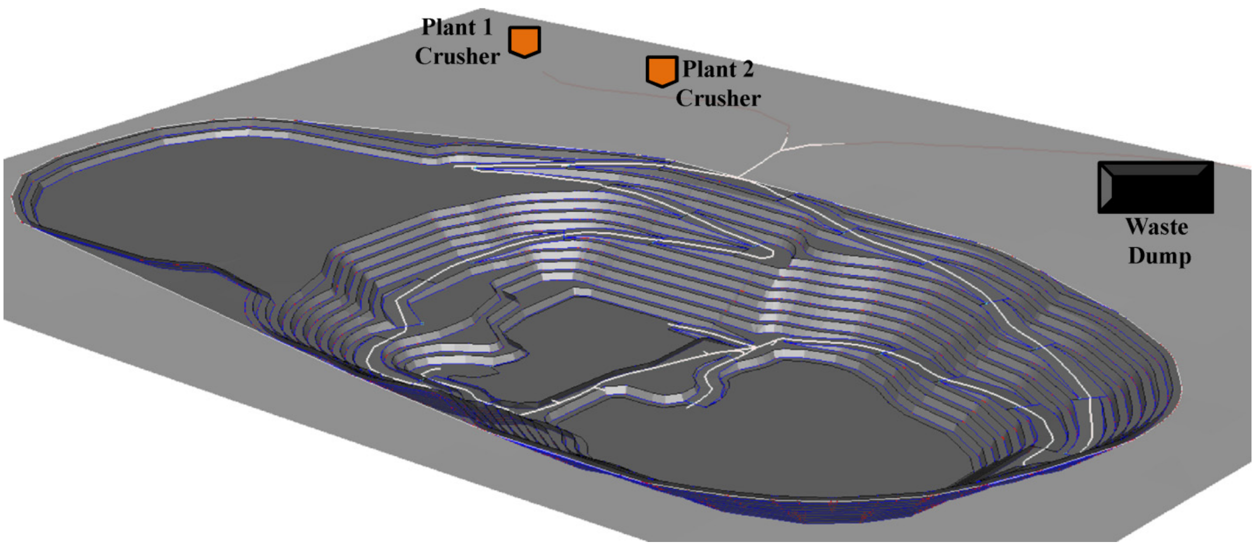

Fig. 3. Mine layout with ramps and road network in year 11

Fig. 3 depicts the mine layout in year 11 of the production with the road network, two plant crushers and a waste dump. The plant crushers require 2000 ton per hour of ore with each having a hopper capacity of 500 ton. Plant 1 and plant 2 crushers are desired to have ore with magnetic weight recovery (MWT) grade of 65% and 75% respectively. Plant 2 is required to get higher priority in meeting the desired grade compared to plant 1. Fig. 4 shows the grade distribution of ore scheduled for year 11 out of which blending objectives need to be achieved.

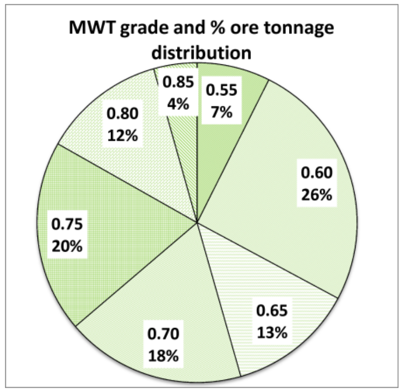

Fig. 4. Percent ore tonnage of MWT grades scheduled in year 11

Mine production operations are carried out in one 12 hour shift daily and 7 days a week. The mine employs a total of 5 shovels with 2 Hit 2500 shovels specifically for ore and 3 Hit 5500Ex shovels only for waste mining. The Hit 2500 shovels have a bucket capacity of approximately 12 ton and a bucket cycle time of about 22 seconds; whereas Hit 5500Ex shovels have a bucket capacity of approximately 22 ton and a bucket cycle time of about 23 seconds.

To haul the material from the faces mine employs 15 Cat 785C and 18 Cat793C trucks with nominal capacities of 140 ton and 240 tons respectively. Cat 785C trucks are locked to ore shovels and thus they may be loaded only by Hit 2500 shovels, and Cat 793C trucks can only be loaded by Hit 5500Ex shovels.

5. Results

The MILGP model is a dynamic decision making tool and is implemented with a simulation model providing it decisions as system state changes and shovel relocations are desired. At this stage, to verify the behavior of the MILGP model correctly, equipment failures and other uncertainties are not included in the simulation model. Also, a higher weight of one is given to plant 2 compared to 0.5 to plant 1 in the MILGP model to meet grade blending requirements as required by the case. The MILGP model is solved using CPLEX (CPLEX, 2014) and discrete event simulation model is developed in Arena simulation package (Arena, 2013).

Dynamic decisions provided by MILGP model were analyzed by examining the simulation results and KPIs related to the objectives considered in the model. Realistic shovel allocation was the prime requirement of the model and its performance greatly rely on it. Shovel positions and the working months were plotted to analyze the allocation decisions made by the model. Fig. 5, Fig. 6, Fig. 7 and Fig. 8 shows the shovels in shaded color, polygon boundaries by solid edges and working (starting) month in numerals for the four benches 1745, 1730, 1610 and 1595 respectively scheduled in the year. Benches 1745 and 1610 overlap over benches 1730 and 1595 respectively, leaving no available faces in the beginning on benches 1730 and 1595 due to vertical dependencies. In the beginning ore shovels 1, 2 and waste shovel 5 are assigned on bench 1610, and waste shovels 3 and 4 start on bench 1745. Ore shovels 1 and 2 remain only on benches 1610 and 1595 as other two benches contain only waste. Also ore on bench 1595 becomes available only after vertical dependencies on bench 1610 are mined.

It can be observed that ore shovels 1 and 2 start from bench 1610, waste mining shovel 3 and 4 start from top bench 1745 and waste mining shovel 5 starts from bench 1610. Bench 1745 and 1730 is mined by shovel 3 and 4, and waste on bench 1610 is mined by shovel 5. A small portion of bench 1610 is mined by shovel 4 in month 10 when it moves down to lower benches. Due to slower mining rate of ore shovels and only one waste shovel on bench 1610, faces were not readily available on bench 1510, causing it to be mined towards the end of the year when all other waste shovels move to it. This cluttering of shovels happen due to lesser number of faces available for shovel allocations towards the end of year, and will be mitigated by bringing in next year's schedule early.

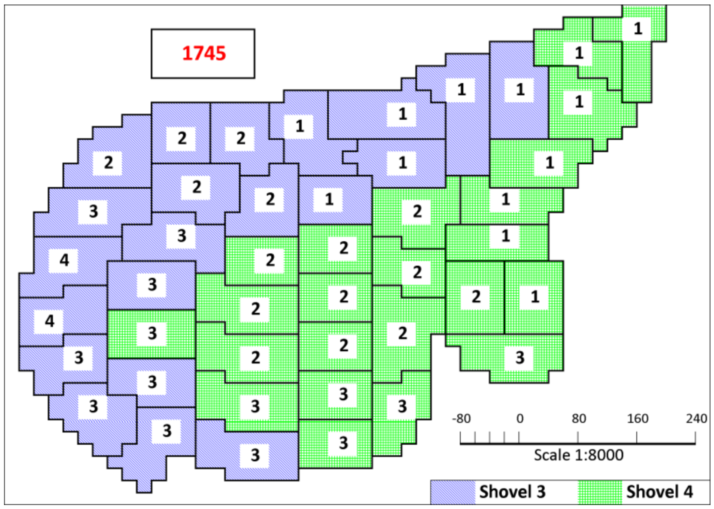

Fig. 5. Shovel positions and corresponding starting month of mining for bench 1745

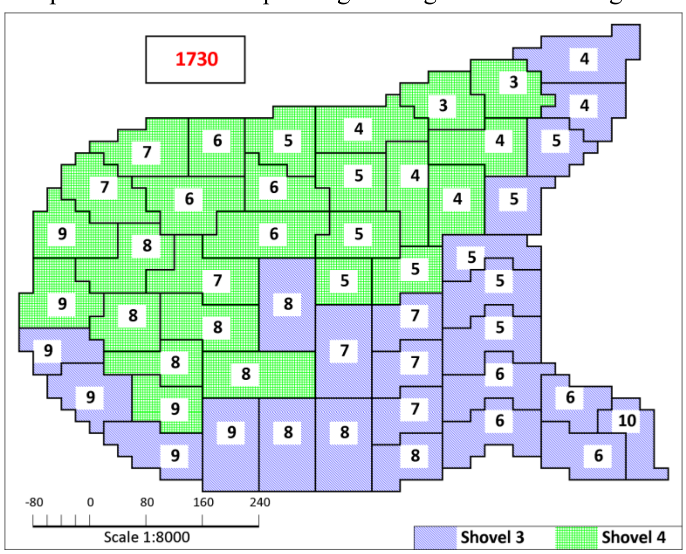

Fig. 6. Shovel positions and corresponding starting month of mining for bench 1730

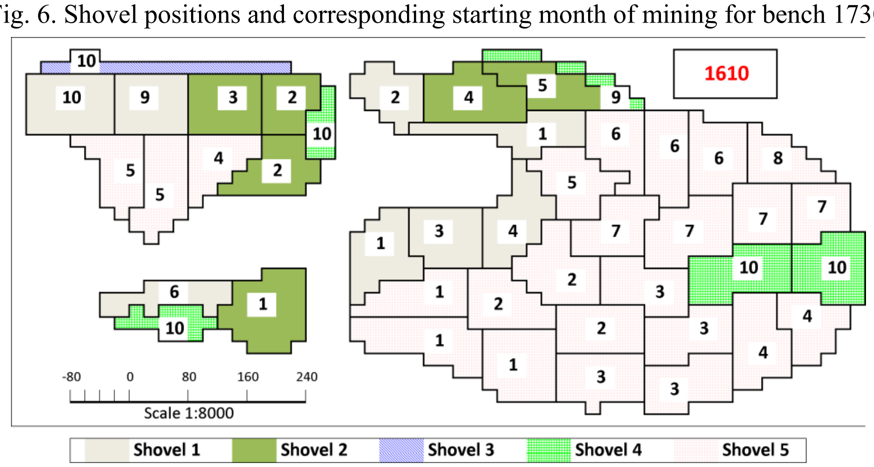

Fig. 7. Shovel positions and corresponding starting month of mining for bench 1610

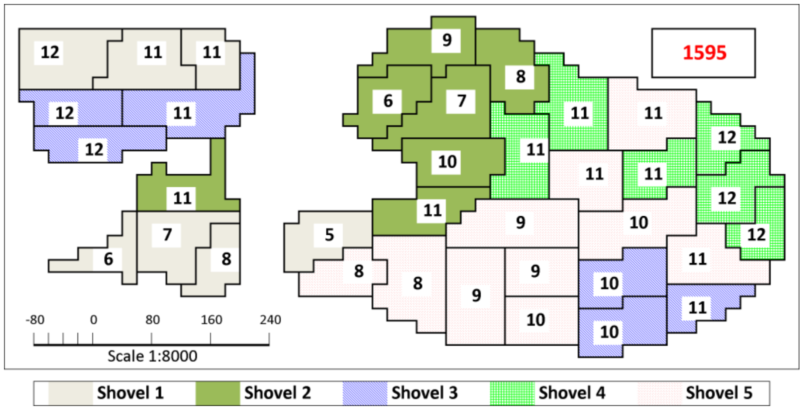

Fig. 8. Shovel positions and corresponding starting month of mining for bench 1595

It can be observed that waste shovels move mostly to the nearest faces, but it is not the case for ore shovels 1 and 2. This happens because of the ore blending objective in the objective function, which gives higher preference on achieving grade blending requirements for plants. An overall analysis of the shovel positions show reasonable and realistic shovel allocations made by the MILGP model.

Considering the tight precedence requirements and very limited available faces, the MILGP model could assign shovels to the faces and at the same time minimize the shovel idle times due to unavailability of faces. The foresightedness in the model let the model foresee the unavailability of faces and allocate the shovels so that other shovels do not encounter idling due to unavailability of faces in the future.

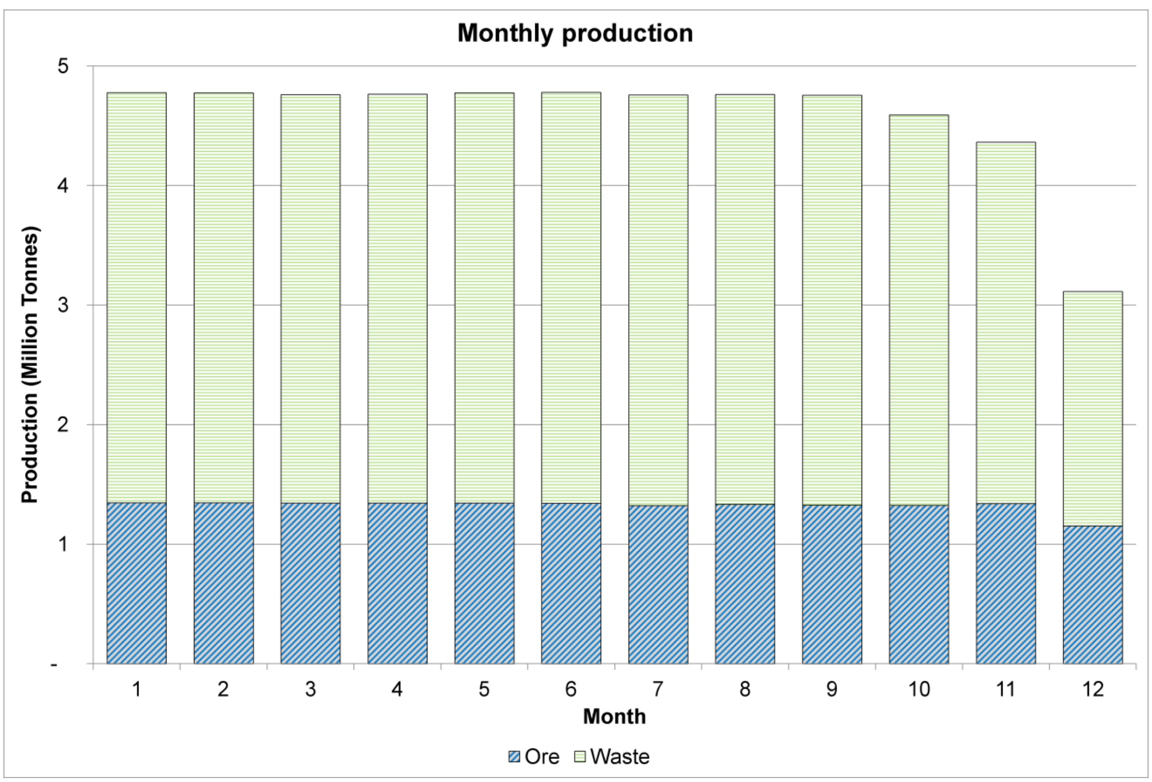

Fig. 9. Monthly ore and waste mining production obtained

Fig. 9 presents the monthly production of the mine, accounting for the production lost due to shovel movements and idle times due to unavailability of the faces. It clearly verifies that the model was capable of achieving its objective of maximum production. Deviation in production towards the end is mostly caused due to unavailability of faces, which would not happen if next year's schedule is brought in early and more faces are available.

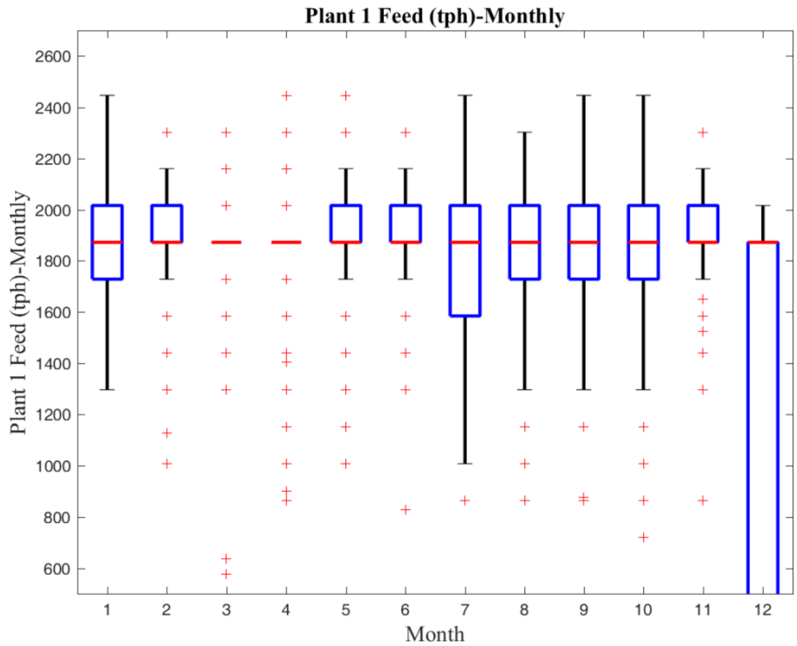

Fig. 10. Box plot showing hourly recorded tonnage (TPH) distribution delivered to plant 1

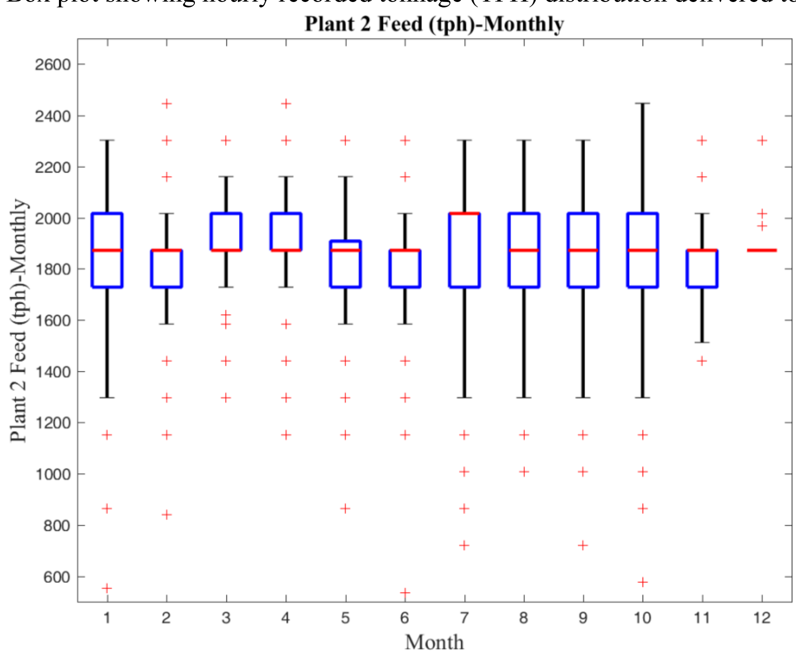

Fig. 11. Box plot showing hourly recorded tonnage (TPH) distribution delivered to plant 2

The simulation model incorporates a truck dispatching system which tries to achieve the flow of trucks to shovels and their respective destinations, as targeted by the MILGP model for desired blending and feed to plants. Fig. 10 and Fig. 11 shows the box plots for ton per hour (TPH) delivered to plants every month. Greater variability is observed at month 12 due to unavailability of ore faces. Analyzing the average TPH delivered to plants, it was verified that the MILGP model could attain the second objective which tries to minimize the deviation in production received at processing plants compared to target.

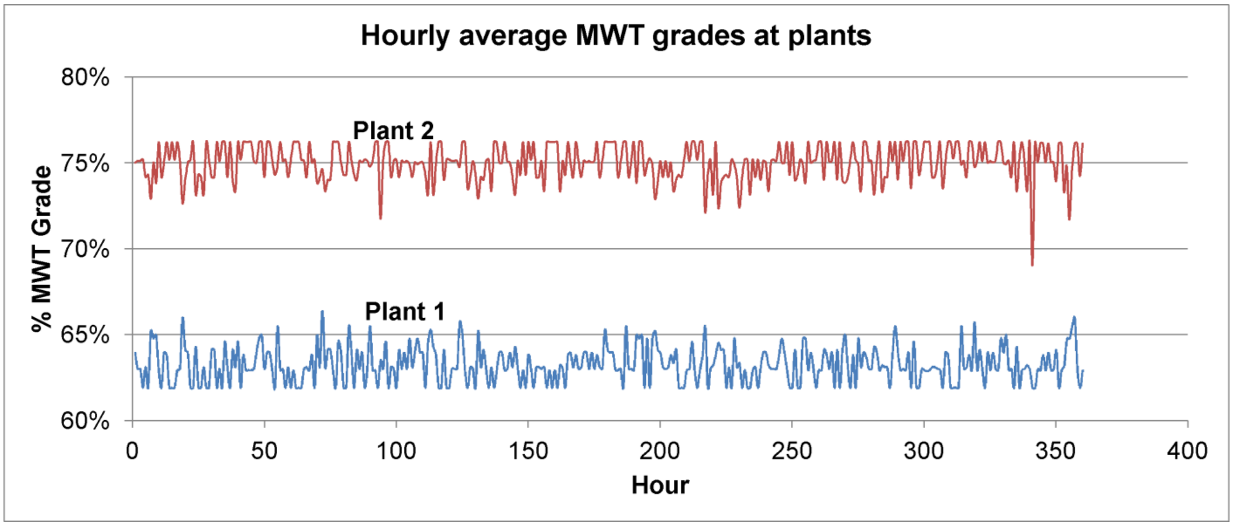

Fig. 12. Average hourly grades at plants for the first month

The most difficult objective of the MILGP model was to deliver the desired grades to the plants, which can only be achieved if suitable combinations of ore faces are mined together in the course of time. Fig. 12 shows the hourly average grades delivered to the plants in the first month and Fig. 13 shows weekly average of grades delivered to the plants for the year. The model results presented here are with higher weight to minimize the grade deviation at plant 2 as desired by the case. Fig. 12 shows that simulation could achieve the truck allocations provided by the MILGP model and average grades delivered were very close to desired grades at the hourly resolution in first month. Average weekly grades in Fig. 13 show that plant 2 received grades as desired except for few weeks in the middle and towards the end. As higher weight was given to grade blending requirements at plant 2, better results are obtained for plant 2, and plant 1 show higher deviations compared to desired grade. Grade blending was also affected by the availability of the suitable faces. It can be observed from Fig. 5 to Fig. 8 that model assigned ore shovels to suitable faces with less priority to movement and higher priority for grade blending as desired. This causes more movement for ore shovels affecting hourly TPH to plants (Fig. 10 and Fig. 11) during movements. As given in Fig. 4, 33% of scheduled ore tonnage was below 65% MWT grade and 36% of scheduled ore tonnage was above 75% MWT grade, which was blended reasonably to achieve the target grades. Compared to grade distribution of scheduled faces (Fig. 4), it can be verified that model could achieve the grade blending objective to a reasonable extent.

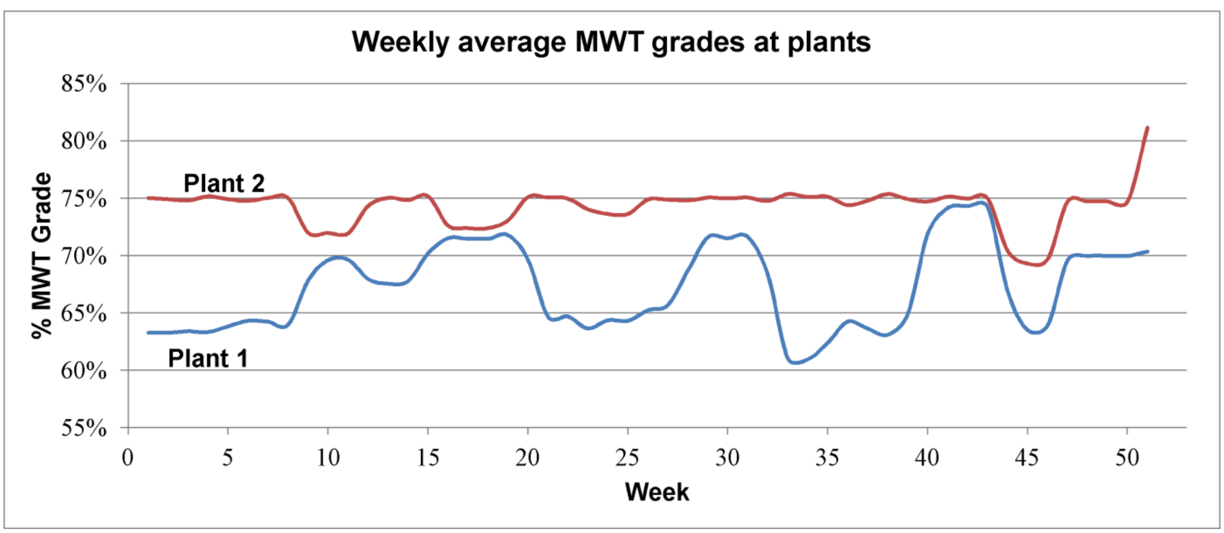

Fig. 13. Average weekly grades delivered to plants for the year

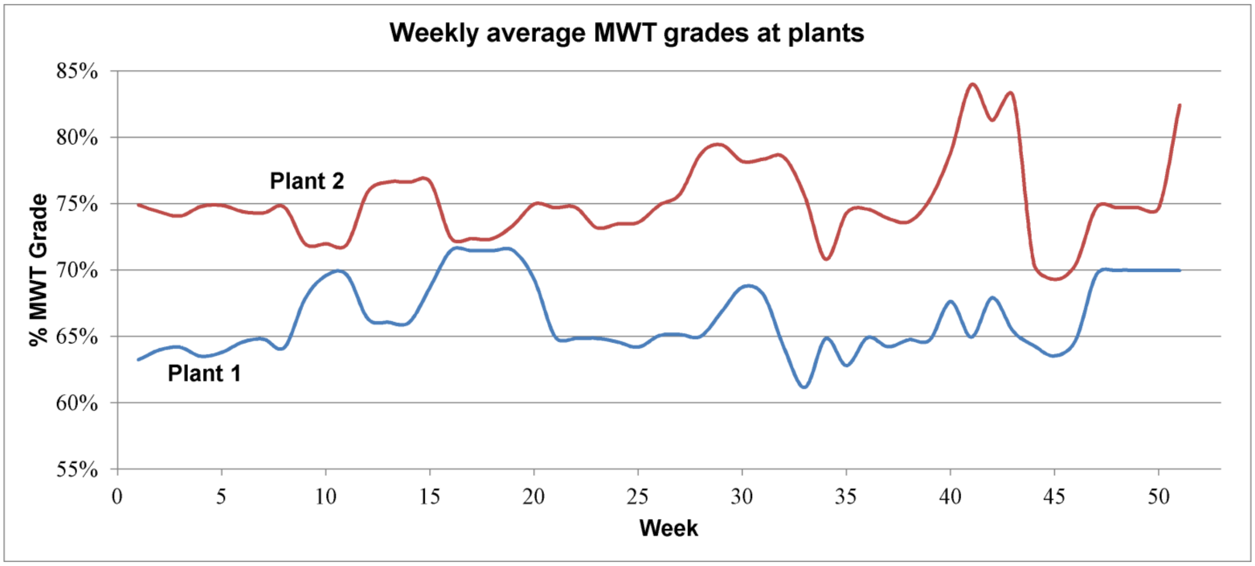

Fig. 14. Average weekly grades delivered to plants with equal grade blending priority to both plants

A second scenario is also run to further analyze the strength of the MILGP model if equal priority is given to both plants to achieve grade blending requirement. Fig. 14 shows the average weekly grades delivered to plants in this scenario. Although grade deviations for plant 1 are less in this scenario, grades at plant 2 becomes poor compared to original scenario. The results obtained in this scenario are not as promising as in original scenario and thus original scenario should be adopted in the operations.

Other KPIs of the system were also analyzed for the year, except month 12 which performed poor due to unavailability of faces and higher idle times. Ore and waste shovels were observed to have an average utilization of 99% and 98% respectively, with average truck utilization being 72%. As no equipment failures were considered for the verification, equipments were available all the time. The use of availability of shovels in this scenario was observed to be 99% due to about 150 hours of shovel idle times in month 10 and 11. This occurs due to the cluttering of all three waste shovels on last bench towards the end of year. The total time spent in movement by all the shovels was obtained to be 78 hrs with an average movement time of 16 hrs per shovel for the whole year.

6. Conclusion and future work

The MILGP model presented in this paper is a unique approach towards short term production planning and scheduling. The bottom-up approach, to generate short term plans by simulating production operations, makes it more practical and provides opportunities for proactive planning by scenario analysis.

The results presented in this paper verify the MILGP model and illustrates the capabilities of the approach in attaining short term and operational objectives. As a future work the model is proposed to implement with a stochastic simulation model incorporating all the uncertainties including equipment failures to verify the model behavior. It is proposed to be made more flexible and user friendly to develop as a tool for short term production planning and analysis purposes.

7. References

[1] Arena. (2013). Version 14.50.00002: Rockwell Automation Inc.

[2] Bjørndal, T., Herrero, I., Newman, A., Romero, C., & Weintraub, A. (2012). Operations research in the natural resource industry. *International Transactions in Operational Research, 19*(1-2), 39-62.

[3] CPLEX. (2014). IBM ILOG CPLEX Optimization Studio Version 12.6: IBM Corporation.

[4] Eivazy, H., & Askari-Nasab, H. (2012). A mixed integer linear programming model for short-term open pit mine production scheduling. *Mining Technology, 121*(2), 97-108.

[5] Elbrond, J., & Soumis, F. (1987). Towards integrated production planning and truck dispatching in open pit mines. *International Journal of Surface Mining, Reclamation and Environment, 1*(1), 1-6.

[6] Fioroni, M. M., Franzese, L. A. G., Bianchi, T. J., Ezawa, L., Pinto, L. R., & de Miranda, G. (2008). *Concurrent simulation and optimization models for mining planning*. Paper presented at the WSC 2008.

[7] Grodzevich, Oleg, & Romanko, Oleksandr. (2006). *Normalization and Other Topics in Multi-Objective Optimization*. Paper presented at the Fields-MITACS Industrial Problems Workshop.

[8] Gurgur, C., Dagdelen, K., & Artittong, S. (2011). Optimization of a real-time multi-period truck dispatching system in mining operations. *International Journal of Applied Decision Sciences, 4*(1), 57-79.

[9] L'Heureux, G., Gamache, M., & Soumis, F. (2013). Mixed integer programming model for short term planning in open-pit mines. [doi: 10.1179/1743286313Y.0000000037]. *Mining Technology, 122*(2), 101-109.

[10] Lestage, P., Mottola, L., Scherrer, R., & Soumis, F. (1993). *A Computerized Tool for Short Range Production Planning in Use at the Mont Wright Operation*. Paper presented at the APCOM International symposium.

[11] Li, Z. (1990). A methodology for the optimum control of shovel and truck operations in open-pit mining. *Mining Science and Technology, 10*(3), 337-340.

[12] Newman, Alexandra M., Rubio, Enrique, Caro, Rodrigo, Weintraub, Andrés, & Eurek, Kelly. (2010). A Review of Operations Research in Mine Planning. *Interfaces, 40*(3), 222-245.

[13] Soumis, F., Ethier, J., & Elbrond, J. (1989). Evaluation of the New Truck Dispatching in the Mount Wright Mine. *21st Application of Computers and Operations Research in the Minerals Industry, SME*, 674-682.

[14] Subtil, R. F., Silva, D. M., & Alves, J. C. (2011). *A Practical Approach to Truck Dispatch for Open Pit Mines.* Paper presented at the APCOM Symposium, Wollongong, NSW.

[15] Tabesh, M., & Askari-Nasab, H. (2013). Automatic creation of mining polygons using hierarchical clustering techniques. [journal article]. *Journal of Mining Science, 49*(3), 426-440.

[16] Temeng, Victor A., Otuonye, Francis O., & Frendewey, James O. (1997). Real-time truck dispatching using a transportation algorithm. *International Journal of Surface Mining, Reclamation and Environment, 11*(4), 203-207.

[17] Temeng, Victor A., Otuonye, Francis O., & Frendewey, James O. (1998). A Nonpreemptive Goal Programming Approach to Truck Dispatching in Open Pit Mines. *Mineral Resources Engineering, 07*(02), 59-67.

[18] Upadhyay, S. P., & Askari-Nasab, H. (2016). Truck-shovel allocation optimisation: a goal programming approach. *Mining Technology, 125*(2), 82-92.

[19] White, J.W., & Olson, J.P. (1986). Computer-based dispatching in mines with concurrent operating objectives. *Mining Engineering, 38*(11), 1045-1053.

8. Appendix

8.1. Notations

Index for variables, parameters and sets

s	index for set of *shovels* ($s = 1, \ldots \hat{S}$)
f	index for set of *faces* ($f = 1, \ldots \hat{F}$)
t	index for set of truck types *trucks* ($t = 1, \ldots \hat{T}$)
k	index for set of material types ($k = 1, \ldots \hat{K}$)
d	index for set of *destinations* (processing plants, stockpiles, waste dumps)
d^c	index for set of crushers/*processing plants* ($d^c = 1, \ldots \hat{P}$)
d^o	index for ore destinations (processing plants and stockpiles)
d^w	index for waste dumps ($d^w = 1, \ldots \hat{W}$)
p	index for periods (p=1,…P)

8.2. Decision variables

To formulate all the system constraints and to represent the system as precisely as possible, while keeping the model linear, following decision variables have been considered.

$a_{s,f,p}$	Assignment of shovel s to face f in period p (binary)
$m_{f,p}$	0 or 1 binary variable if face f is mined out in period p
$y_{s,p}$	0 if $r_{s,p}^{rem}$ is greater than 0, else 1
$n_{t,f,d}$	Number of trips made by truck type t, from face f, to destination d (integer) in first period
$x_{s,f,d,p}$	Fraction of tonnage at face f sent by shovel s, to destination d in period p
$x_{s,p}^{-}$	Fraction of maximum capacity of shovel s less produced in period p
$\delta_{d^c,p}^{-}, \delta_{d^c,p}^{+}$	Negative and positive deviation in production received at processing plants d^c in period p, as fraction of processing plant capacities
$g_{k,d^o,p}^{-}, g_{k,d^o,p}^{+}$	Negative and positive deviation in tonnage content of material type k compared to tonnage content desired, as per desired grade, at ore destinations d^o in period p
$l_{f,p}$	Tonnage of material available at face f at the start of period p
$r_{s,p}$	Movement time (minutes) for shovel 's' in period 'p' to go to next assigned face
$r_{s,p}^{rem}$	Remaining movement time (minutes) to be covered in next period

$r_{s,p}^{act}$ Actual movement time (minutes) covered in period 'p'

8.3. Parameters

T Decision time frame (hr)

Fi_s Face where shovel 's' is initially located (start of the optimization)

X_s Shovel bucket capacity (ton)

X_s^+ Maximum possible shovel production in decision time frame 'T' (ton)

L_s Shovel loading cycle time (seconds)

S_s Movement speed of shovel (meter/minute)

α_s^S Shovel availability (fraction)

Γ_{f^1,f^2}^F Distance between faces (meters), calculated as linear distance between faces on the same bench, and following the haul road and ramps between faces on different benches.

N_f^F Number of precedence faces required to be mined before mining face f

Z_{d^c} Maximum capacity of the crushers/processing plants (ton/hr)

$\Lambda_{d^c}^+$ Maximum positive deviation in tonnage acceptable at crushers/processing plants (ton/hr)

$\Lambda_{d^c}^-$ Maximum negative deviation in tonnage acceptable at crushers/processing plants (ton/hr)

G_{k,d^o} Desired grade of material types at the ore destinations

$\bar{G}_{f,k}$ Grade of material type 'k' at face 'f'

O_f Tonnage available at face f at the beginning of optimization (ton)

$O_{\min}$ Minimum material at face below which a face is considered mined

Q_f 1 if material at face is ore, 0 if it is waste (binary parameter)

H_t Tonnage capacity of truck type t

J Flexibility in tonnage produced, to allow fractional overloading of trucks (ton)

$M_{t,s}^t$ Binary parameter, if truck type t can be assigned to shovel s

N_t^T Number of trucks of type t

α_t^T Truck availability (fraction)

$\bar{T}_{t,f,d}$ Cycle time of truck type 't' from face 'f' to destination 'd', averaged over all working shovels and following the haul road network (minutes)

ϕ_s 0 or 1 binary variable if shovel s is working or failed

M_s^{ore} Binary parameter, if shovel s is locked to an ore face

W_i	Normalized weights of individual goals (i = 1, 2, 3, 4) based on priority
ε	A very small decimal value to formulate strict in-equality (depending on constraint)
BM	A very large number (depending on constraint)

Incorporating Cut-off Grade Optimization into Oil Sands Production Scheduling

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Abstract

In pursuance of achieving the maximum benefit in oil sands mining, the long-term production schedule should have the time and the sequence of removing the ore, dyke and waste material. In long-term production scheduling, determining the optimum cut-off grade profile is an important aspect. Based on regulatory requirements, all the material containing more than 7% Bitumen should be mined. Cut-off grade optimization is used to generate an optimum grade schedule with the purpose of specifying the cut-off grade, duration of mining of the grade and tonnage mined during the mine life. This research developed a heuristic model that generates an optimum cut-off grade policy and a schedule for ore and waste material as well as overburden, interburden and tailings coarse sand dyke material. The application of the model to a case study proves its ability to maximize the Net Present Value of the operation through cut-off grade optimization. Scenarios investigated includes: no stockpiling; stockpiling and reclaiming at the end of mine life; and stockpiling with limited reclamation duration. The first two scenarios have similar cut-off grades but the second scenario had one more year mine life because of utilization of the stockpile after the mining operation. The third scenario had the highest cut-off grade profile compared to the others. The optimum schedule can subsequently be used as input for medium and short-term production scheduling and waste management.

1. Introduction

Surface mining accounts for a considerable amount of the produced minerals to meet the increasing need of resources of the high-tech society. Extracting minerals from earth whereby the ore body is accessed by opening a large stretch of ground to expose the ore to air is known as surface mining or open pit mining (Shishvan and Sattarvand, 2015). The mine plan can be categorized as; short-term, medium-term and long-term. The long-term production plan refers to the optimized scheduling of extraction of blocks which lie in the final pit limit in a way that the Net Present Value (NPV) of the deposit is maximized. The results of the long-term production planning process are used as guides for medium and short-term planning (Ben-Awuah and Askari-Nasab, 2011).

Cut-off grade determination is an essential aspect of optimizing the mine strategy and should be an outcome of the optimization process. However, commonly in the mining industry a cut-off grade is calculated prior to mine planning and is used as an input for the strategic plan (Hall, 2014).

Determining the cut-off grade policy is one of the most important steps for optimizing the long-term production plan since it is the criterion that separates ore material from waste material. Materials with a grade value higher than the cut-off grade value are considered as ore and materials with a grade value lower than the cut-off grade value are classified as waste. The aim of determining the optimum cut-off grade profile is to achieve economic goals such as maximizing the NPV of the operation with respect to some constraints. Each operation has its own constraints such as mining capacity, processing capacity, refinery capacity, environmental issues and extraction sequence.

One of the simplest methods to calculate the cut-off grade is called break-even calculation. Although break-even cut-off grade is widely used in mining industry, it does not guarantee generating the maximum NPV of the deposit. The grade at which the obtained revenue is equal to the cost of generating that revenue is called break-even cut-off grade. Equation 1 shows the simple break-even calculation. The break-even calculation is only based on economic parameters and it does not include the mining, processing and refinery capacity and the geology of the deposit.

$$g_{BE} = \frac{\cos t}{(price - selling \cos t) \times \text{recovery}} \tag{1}$$

Poniewierski and Hall (2016) stated that break-even calculation is not accurate enough. They illustrated that an error of 0.1 gram per tonne in the break-even calculation for a low grade gold mine can result in 50-60 percent of the ore material being considered as waste. The main two reasons which can cause errors in the break-even calculation are the fixed recovery and the exclusion of the sustaining capital costs. The fixed recovery percentage is being used in calculating the break-even grade but as a matter of fact, low grade materials and high grade materials do not have the same recovery percentage. In addition, excluding the sustaining capital costs for maintaining the capital items during the life of the equipment will result in noticeable errors in the break-even calculation (Poniewierski and Hall, 2016).

As mentioned earlier, the break-even calculation does not include the two sets of parameters, geology and operational capacities. In 1950, Mortimer described a new cut-off grade model which included geology parameters or grade distribution and cost parameters. He targets two goals in his model: the first goal is that the minimum grade of material must pay for itself and the second goal is that a minimum profit per tonne must be provided by the average grade of material (Mortimer, 1950).A general cut-off grade model was introduced in 1964 by Lane which accounts for all the parameters including costs, grade distribution and operational capacity. The goal of Lane’s model is to maximize the NPV which is the most common goal in mining industry. He defined that any mining operation has three stages: mining, processing and refinery. In his model, six potential optimum cut-off grades are calculated. The first three cut-off grades are called limiting economic cut-off grades and they are directly calculated based on economic parameters. The second three cut-off grades are called balancing cut-off grades and they are dependent on grade distribution of the deposit. Lane (1964) introduced an algorithm to find the optimum cut-off grade between the six potential grades. It has been proven that it is only by applying some optimization methods like Lane’s model that the precision of cut-off grade decision can be guaranteed (Lane, 1964, 1988, 1997; Hall, 2014). Lane's model is used as the starting point of this research. This paper introduces a cut-off grade optimization model that integrates concurrent production scheduling and waste disposal planning with limited stockpiling duration.

The next section of this paper covers the literature on the application of cut-off grade optimization in mine planning. A brief overview of oil sands mining will be discussed in section 3. The problem definition will be presented in section 4. Section 5 outlines the methodology for the cut-off grade optimization model. This is followed by a section on the implementation of a cut-off grade optimization model that features production scheduling and waste disposal planning as applied in oil sands mining. In section 7, a case study presents an application of the cut-off grade optimization model and the generated production schedule. The paper concludes with a discussion of results and future research work.

2. Summary of Literature Review

The most important economic criterion that separates ore from waste material is the cut-off grade. It specifies the amount of material that goes to the processing plant and to the waste dump (King, 1999). If the cut-off grade is determined too low it will result in increasing the life of the operation with no economic justification. On the other side, if the cut-off grade is set too high it will make some economic material to be considered as waste (Bascetin and Nieto, 2007). Therefore, choosing the optimum cut-off grade has a significant impact on the economic aspect of the operation.

The simple break-even calculation can generate the processing cut-off grade within the pre-defined pit limit. It has been proven that break-even calculation cannot maximize the NPV of the operation since it ignores the geology of the deposit and the operational constraints. The results of the simple break-even calculation will generate a constant cut-off grade schedule for the life of the mine (Taylor, 1972; Poniewierski and Hall, 2016). In 1964, Lane developed a cut-off grade optimization model which can consider all the required parameters such as economic parameters, grade-tonnage distribution and operational capacities. The objective function of the Lane's model is to maximize the NPV of the operation with respect to capacity of the mining, processing and refinery. He considered the concept of opportunity cost in his model. Hall (2014) stated that "the concept of opportunity cost is rigorously accounted for to indicate to what extent future production can be deferred to immediately treat additional material as ore". Lane's model maximizes the NPV of the operation and generates a dynamic cut-off grade policy based on the concept of opportunity cost for the life of mine. During the early years of mining operation, Lane's model generates a higher cut-off grade and this decreases towards the end of the operation's life (Lane, 1964). The dynamic nature of the 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 (Asad et al., 2016). Many mine planning software use the Lane's theory in order to specify the optimum cut-off grade policy (Whittle, 1999).

Dadgelen (1992) presented the steps of Lane's theory for the case of a hypothetical gold deposit, where the operation's capacity is only limited by the processing plant. He showed the difference between using the dynamic cut-off grades versus the constant break-even cut-off grade. He stated that the optimized cut-off grade policy generates 90% higher NPV than the simple break-even cut-off calculation. He also presented the complete steps of the Lane's theory in the following year (Dadgelen, 1993).

During the past years many researchers such as Osanloo and Gholamnejad, tried to incorporate environmental issues and related cost in the cut-off grade calculation. Osanloo et al. (2008) modified the basic Lane's model to consider two different destinations for acid and non-acid wastes. They considered the cost of dumping different kinds of wastes in their formulation. Their case study showed an improvement of NPV compared to Lane's basic model as well as the environmental sustainability for the operation.

Gholamnejad used the Lane's theory in order to determine the optimum cut-off grade in the presence of rehabilitation cost. He stated that, by considering the rehabilitation cost, the optimum cut-off grade will be reduced. He showed that the amount of ore will increase and the amount of waste will decrease by considering the rehabilitation cost. Gholamnejad claimed that the total NPV of the project will be increased. He mentioned that the rehabilitation cost should be determined prior to optimization, so it can be used to generate more realistic results (Gholamnejad, 2008, 2009).

In the algorithm presented by Lane, the mining, processing and refinery capacities are assumed to be constant. Abdollahisharif et al., (2012) tried to introduce variable production capacities into Lane's model. He compared his model with Lane's basic model and the modified version of Lane's model developed by Gholamnejad (2009). Due to the variable capacity, the NPV was higher than the two models.

During the past four decades, many researchers have developed extensions to Lane's model for deposits with single economic mineral. Mol and Gillies (1984) developed a model to maximize material blending to gain the required grade specification which is defined by the market driven contracts. The concept of opportunity cost was modified by introducing an optimization factor to deal with the convergence of NPV in Lane's model iterative process. The model made an enhancement in the NPV of the operation (Nieto and Bascetin, 2006). The generalized reduced gradient algorithm was used to generate a solution to the modified model (Bascetin and Nieto, 2007).

In 1984, Lane introduced an important extension to the original model. The new model was capable of calculating the cut-off grades for multiple economic mineral deposits. For instance, a deposit with two economic minerals requires refinery detail for two minerals and so the formulation needs some modifications. In order to provide solution for such kind of problems, Lane used the grid search technique and provided a case study to illustrate the implementation of the approach (Lane, 1984, 1988).

Asad (2005) also developed a model as an extension to Lane's original theory for cut-off grade optimization for deposits considering two economic minerals with stockpiling option. The stockpile acts as an additional push back when the mining operation is finished. The material with grade between break-even grade and optimum cut-off grade is sent to the stockpile in each year. He mentioned that long-term stockpiling can cause series of problems such as leaching, deterioration of material and oxidation which can cause poor recoveries in the treatment process. He showed that his model can increase the NPV of the mining operation in the hypothetical case study (Asad, 2005). He used the concept of varying the annual commodity price and the operating costs. He presented the effects of these modifications on the NPV of the mining operation by applying the model to a hypothetical copper deposit (Asad, 2007). Asad and Topal (2011) completed the Asad's 2007 model by adding the stockpiling scenario. They used the stockpile after finishing the mining operation. They demonstrated the advantages of the model by comparing the cut-off grade policy with and without stockpiling option and the improved NPV of the operation.

Many studies have been undertaken with improvements to Lane's model for deposits with single and multiple economic minerals. In the case of oil sands mining, the planning engineer is required to schedule both ore, overburden and interburden; and the stockpiled material must be processed within a limited timeframe due to oxidation that affects processing recovery efficiency. This paper presents an extension of Lane's model that features concurrent production scheduling and waste management with limited stockpile duration.

3. Oil sands mining

For open pit design and scheduling, the material in the orebody is divided into a three-dimensional array of cubical blocks called a block model. The block model has some attributes such as rock type, economic data, densities and grade which can be represented numerically (Askari-Nasab et al., 2011). The block model dimensions are selected based on deposit geology and equipment size. An oil sands deposit contains five main rock types namely: 1) Muskeg/peat, 2) Pleistocene unit, 3) Clear water formation, 4) McMurray formation and 5) Devonian carbonates. The desired mineral is bitumen which is contained in the McMurray formation. In order to get access and mine the McMurray formation, the overburden material which includes muskeg, pleistocene unit and clear water formation should be removed. After mining and processing the oil sands ore, more than 80% of the ore are deposited in tailing dams (Masliyah, 2010). The significant amount of tailings material has caused several environmental issues. The regulatory requirement by Alberta Energy Regulator (AER) Directive 082 (formerly interim directive ID 2001-7) requires oil sands mining companies to integrate their waste management strategy into their long-term production plans. It also requires mining companies not to leave behind any material containing more than 7% bitumen (Ellis, 2016). In order to reduce the environmental footprints, dyke construction should take place simultaneously as the mine advances and the area of each push back become available for dyke construction. The material required for the dyke construction mainly comes from mining operation. The dyke material includes overburden (OB), interburden (IB) and tailings coarse sand material (TCS) (Ben-Awuah and Askari-Nasab, 2011; Ben-Awuah et al., 2012). The above mentioned regulatory requirement and environmental issues make the waste management strategy as a necessary part of the long-term production planning.

Figure 1 illustrates the strategic production planning for an oil sands deposit containing K mining-cuts and M push backs. Mining-cuts are made up of blocks within the same level that are grouped together based on their attributes; location, rock type and grade using an agglomerative hierarchical clustering algorithm by Tabesh and Askari-Nasab (2011).

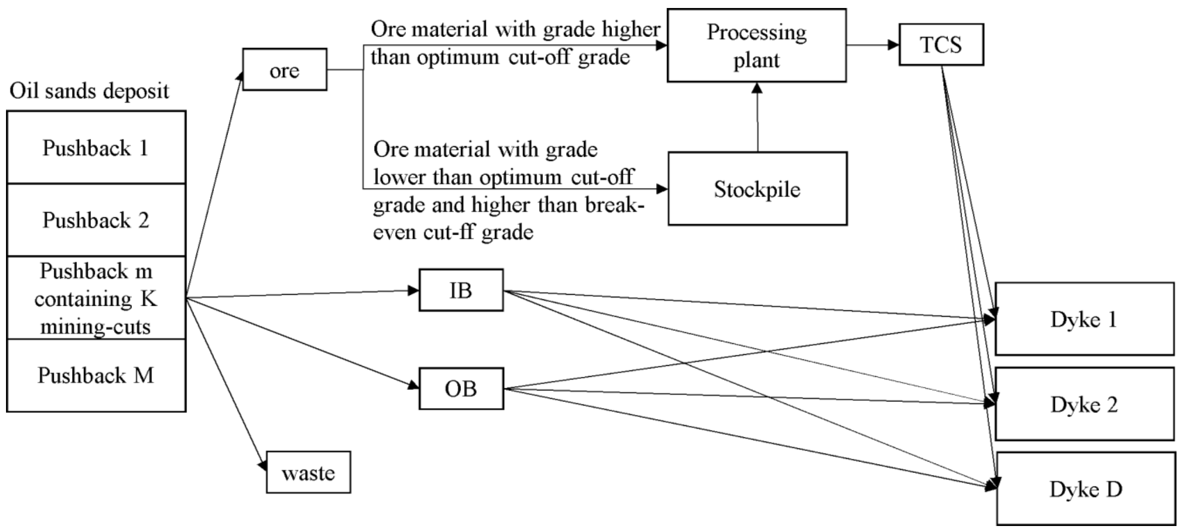

Figure 1 - Material flow for oil sands production planning and waste management modified after Ben-Awuah and Askari-Nasab (2013)

Lowest acceptable grade is the break-even grade of the oil sands operation taking into consideration the grade-recovery relationship. Initial scheduling analysis with Whittle Milawa Balanced (Gemcom Software, 2013) generates a lowest acceptable cut-off bitumen grade of 6%. Figure 2 shows the processing plant recovery factor based on average weight percent bitumen content according to Directive 082 (Ellis, 2016). Material with bitumen grade less than 6%, have recovery less than 31% and hence are not economic for processing. Each mining-cut contains: 1) ore which is the material with bitumen grade higher than 6%, 2) TCS which is the dyke material from processed ore, 3) OB and IB which are the material with bitumen grade less than 6% and meet the dyke construction material requirements and 4) waste.

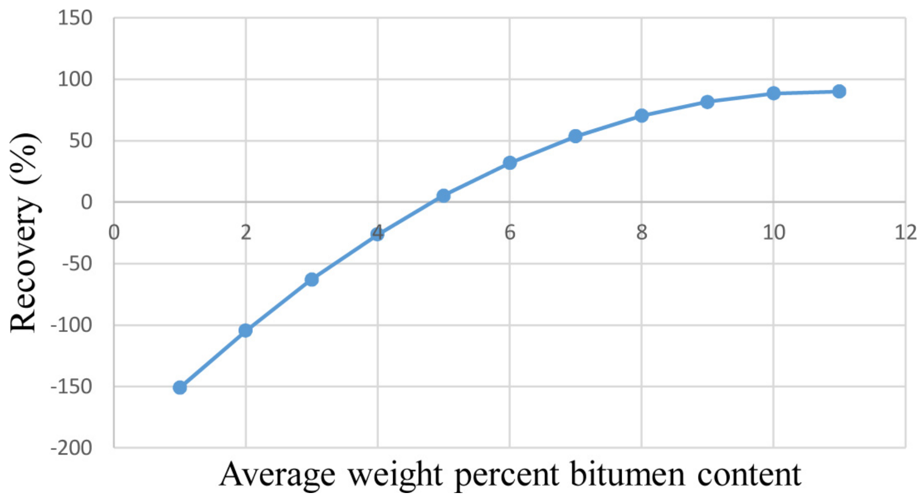

Figure 2 - Processing plant recovery factor

4. Problem definition

The main problems in oil sands mining that this paper is addressing can be classified into three categories:

1- Determining the life of mine optimum cut-off grade profile and corresponding ore tonnages to maximize the NPV of the operation.
2- Determining the dyke material schedule for dyke construction.
3- Assessing the impacts of stockpiling and stockpile reclamation with limited duration.

In order to maximize the NPV of the oil sands mining operation with respect to processing capacity, an extension of the Lane's model will be developed to determine the optimum cut-off grade policy in presence of waste management for dyke construction and stockpiling with limited duration. The cut-off grade optimization model developed in this work considers stockpile rehandling cost, waste management cost and generates a production schedule for multiple material types. The model is implemented for an operation which is limited by the processing plant, as is mainly the case in oil sands mining.

The result from the cut-off grade optimization can be used as guidance for defining the input parameters in oil sands production scheduling and waste management for medium and short-term mine planning.

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

Lane (1964) developed a comprehensive model to determine the optimum cut-off grade and the amount of material to be mined, processed and refined in each period for the life of mine. The optimum cut-off grade policy is dependent on the economic parameters, the limiting operational capacities and the grade distribution of the deposit. Using stockpiling can improve the NPV of the operation significantly. The stockpiled material can be reclaimed in two ways (Ali and Khan, 2004):

1. The stockpile is reclaimed after pit mining is finished;
2. The stockpile is reclaimed simultaneously during active pit mining.

We are going to present the modified version of Lane's model referred to as the integrated cut-off grade optimization (ICOGO) model. The ICOGO model for oil sands mining incorporates waste management for dyke construction and limited stockpile duration during the cut-off grade optimization process. The two stockpiling scenarios outlined will be presented in addition to a no stockpiling scenario. Since oil sands ore has grade dependent processing recovery characteristics, the ICOGO framework features the use of a weighted average recovery factor.

5.1. Notations

The following are the details of notation used in the formulation of the ICOGO model.

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

d the discount rate.

F the annual fixed cost.

n the index of scheduling period.

f_n the opportunity cost of the year n.

g_{avg_n} the average head grade of the year n.

g_{BE} the break-even cut-off grade.

g_l the minimum acceptable cut-off grade.

g_m the mining limited cut-off grade.

g_p the processing limited cut-off grade.

g_r the refinery limited cut-off grade.

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

kc the cost of mining a tonne of ore from stockpile.

kd the duration of stockpiling the material.

kt_n the amount of material (tonnes) send to the stockpile in period n.

kt_{n-kd} the amount of material (tonnes) reclaimed from the stockpile in period n.

mc the cost of mining a tonne of waste.

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

pr_n the annual profit.

qk the amount of reclaimed material from stockpile

QM the maximum mining capacity in terms of tonnes per year

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 maximum refinery capacity in terms of tonnes per year

qr the amount of material to be refined (tonnes)

r_{avg} the weighted average processing recovery.

R_{IB} the ratio of the IB dyke material to the total amount of waste.

R_{OB} the ratio of the OB dyke material to the total amount of waste.

R_{TCS} the ratio of the TCS dyke material to the total amount of ore.

sp the selling price per unit of product.

sc the refinery and selling cost per unit of product.

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

5.2. Optimum Cut-Off Grade

Using the lowest acceptable cut-off grade of 6%, material in the final pit limit is classified as ore, dyke material and waste. The tonnages of ore, OB, IB, TCS and waste material are estimated from the block model. In order to incorporate the costs of waste management into the cut-off grade optimization process, we need to relate the ratio of the amount of dyke construction material to the total amount of ore and waste. Equation (2) shows the ratio of the TCS dyke material to the total amount of ore; Equation (3) and (4) show the ratio of the OB and IB dyke material to the total amount of waste, respectively.

$$R_{TCS} = \frac{Total\ amount\ of\ TCS\ dyke\ materail}{Total\ amount\ of\ ore} \tag{2}$$

$$R_{OB} = \frac{Total\ amount\ of\ OB\ dyke\ materail}{Total\ amount\ of\ waste} \tag{3}$$

$$R_{IB} = \frac{Total\ amount\ of\ IB\ dyke\ materail}{Total\ amount\ of\ waste} \tag{4}$$

A mining operation is made up of three stages: mining, processing and refinery. Each stage is limited by its costs and operational capacity. Lane (1964) established that any operation can have two groups of cut-off grades: Limiting cut-off grades and Balancing cut-off grades. These are modified in the ICOGO model for oil sands mining.

5.3. ICOGO Limiting Cut-off Grade

These cut-offs are calculated based on the economic parameters. Each of the mining, processing and refinery stages can be the limiting factor for mine production. Equation (5) shows the profit expression for mining and waste management operations.

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

$$pr = (sp - sc)qr - pc.qp - mc.qm - tc.R_{TCS}.qp - bc.R_{OB}.(qm - qp) - ic.R_{IB}.(qm - qp) - FT \tag{5}$$

- If maximum mining rate is the overall constraint:

  The time (mine life) required to mine the total amount of material when the mining rate is the main constraint is calculated by Equation (6). The amount of product is determined based on the amount of ore that is sent to the processing plant. Equation (7) shows the relation between the amount of ore and the amount of product.

$$T_m = \frac{qm}{QM} \tag{6}$$

$$qr = g_{avg}.r_{avg}.qp \tag{7}$$

For mining limited cut-off grade, Equation (11), can be calculated by substituting Equations (6) and (7) into Equation (5); and take the derivative of Equation (8) with respect to the grade and set it to zero for optimum cut-off grade.

$$pr = \left(\left(sp - sc\right).g_{avg}.r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB}\right).qp - \left(mc + bc.R_{OB} + ic.R_{IB} + \frac{F}{QM}\right).qm \tag{8}$$

$$\frac{dpr}{dg} = \left(\left(sp - sc\right).g_{avg}.r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB}\right).\frac{dqp}{dg} - \left(mc + bc.R_{OB} + ic.R_{IB} + \frac{F}{QM}\right).\frac{dqm}{dg} = 0 \tag{9}$$

The cut-off grade affects the amount of processing material and product. The amount of material to be mined is independent from the grade which makes $\frac{dqm}{dg} = 0$, so to make the Equation (9) equal to zero, Equation (10) should be zero, which gives us the mining limited cut-off grade.

$$\left(\left(sp - sc\right).g_{avg}.r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB}\right) = 0 \tag{10}$$

$$g_m = \frac{pc + tc.R_{TCS} - bc.R_{OB} - ic.R_{IB}}{\left(sp - sc\right).r_{avg}} \tag{11}$$

- If maximum processing rate is the overall constraint:
  The time (mine life) is determined by the processing rate using Equation (12). For processing limited cut-off grade, Equation (15), can be calculated by substituting Equations (7) and (12) into Equation (5); and take the derivative of Equation (13) with respect to the grade and set it zero for optimum cut-off grade.

$$T_p = \frac{qp}{QP} \tag{12}$$

$$pr = \left(\left(sp - sc\right).g_{avg}.r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP}\right).qp - \left(mc + bc.R_{OB} + ic.R_{IB}\right).qm \tag{13}$$

Similarly, for $\frac{dpr}{dg} = 0$, Equation (14) should be zero which gives us the processing limited cut-off grade.

$$\left(\left(sp - sc\right).g_{avg}.r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP}\right) = 0 \tag{14}$$

$$g_p = \frac{pc + tc.R_{TCS} - bc.R_{OB} - ic.R_{IB} + \frac{F}{QP}}{\left(sp - sc\right).r_{avg}} \tag{15}$$

- If maximum refinery rate is the overall constraint:
  The time (mine life) is determined by the refinery rate calculated by Equation (16). For refinery limited cut-off grade, Equation (19), can be calculated by substituting Equations (7) and (16) into Equation (5); and take the derivative of Equation (17) with respect to the grade and set it zero for optimum cut-off grade.

$$T_r = \frac{qr}{QR} \quad (16)$$

$$pr = \left(\left(sp - sc - \frac{F}{QP} \right) . g_{avg} . r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} \right) . qp - \left(mc + bc.R_{OB} + ic.R_{IB} \right) . qm \quad (17)$$

Similarly, for $\frac{dpr}{dg} = 0$, Equation (18) should be zero which gives us the refinery limited cut-off grade.

$$\left(\left(sp - sc - \frac{F}{QP} \right) . g_{avg} . r_{avg} - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} \right) = 0 \quad (18)$$

$$g_r = \frac{pc + tc.R_{TCS} - bc.R_{OB} - ic.R_{IB}}{\left(sp - sc - \frac{F}{QR} \right) . r_{avg}} \quad (19)$$

The optimal production and waste disposal schedule with optimum cut-off grade policy can be generated with an iterative algorithm which is presented in the section 6.1 using an oil sands case study.

6. Implementation of the ICOGO Model

In the case of oil sands mining, mine production is mainly limited by the processing plant capacity. Dadgelen (1992) presented a model to optimize the cut-off grade by Lane's method when the mining operation is only limited by the processing capacity (SME, 2011). Using Lane's model, we present a modified version of Dagdelen's algorithm in the ICOGO model. The ICOGO model generates an optimum production schedule for oil sands mining considering waste management for dyke construction and stockpiling with limited duration.

6.1. Steps of Iterative Algorithm

1. Take the input parameters including: economic parameters, operational capacities and grade-tonnage curve.

   $$mc, pc, sc, kc, sp, tc, bc, ic, R_{TCS}, R_{OB}, R_{IB}, r_{avg}, d, F, QM, QP, QR$$

2. Determine the lowest acceptable grade, g_l .
3. Calculate the opportunity cost $\left(f_n \right)$ by Equation (20). Set the initial $NPV_n = 0$.

   Cut-off grade should pay for the opportunity cost of not receiving the future cash flow from higher grade material in addition to the processing and waste management cost.
4. Determine processing cut-off grade in the year n by Equation (21).

$$f_n = \frac{d \times NPV_n}{QP} \quad (20)$$

$$g_{p_n} = \frac{pc + tc.R_{TCS} - bc.R_{OB} - ic.R_{IB} + f_n + \frac{F}{QP}}{\left(sp - sc \right) . r_{avg}} \quad (21)$$

5. If the calculated g_{p_n} is less than g_l , set the $g_{p_n} = g_l$

6. From the most recent grade-tonnage curve determine:

- q_o : The amount of ore tonnage above the cut-off grade g_{p_n}
- g_{avg_n} : The weighted average ore grade above the cut-off grade g_{p_n}
- q_w : The amount of waste tonnage below the cut-off grade g_{p_n}
- $R_{sr} = \dfrac{q_w}{q_o}$: The stripping ratio

7. In this step the stockpile option should be decided; 1) without stockpile, 2) utilizing the stockpile after the mine is exhausted or 3) utilizing the stockpile simultaneously with the mining operation.

   7.1) Without stockpile:

- If $q_o \geq QP$
- For the year n set the $qp = QP$
- Otherwise set $qp = q_o$
- Calculate the amount to be mined in year n by Equation (22)

$$qm = qp.\left(1 + R_{sr}\right) \tag{22}$$

- Adjusting the grade-tonnage curve without changing it's shape: subtract the proportionate amount of qp from the ore tonnes and the proportionate amount of $\left(qm - qp\right)$ from the current waste tonnes of the grade-tonnage curve.
- Calculate the annual profit for the mining operation by Equation (23)

$$pr_n = \left(\left(\left(sp - sc\right).g_{avg_n}.r_{avg}\right) - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP}\right)qp - \left(mc + bc.R_{OB} + ic.R_{IB}\right)qm \tag{23}$$

   7.2) Utilizing the stockpile after the mine is exhausted:
   We will consider the stockpile as an extra pushback, when the mine is exhausted.

- If $q_o \geq QP$
- For the year n set the $qp = QP$
- Otherwise set $qp = q_o$
- Calculate the amount to be mined in year n by Equation (22)
- Adjusting the grade-tonnage curve without changing it's shape: subtract the proportionate amount of qp from the ore tonnes and the proportionate amount of $\left(qm - qp\right)$ with grades between g_{p_n} and g_l, stockpile tonnes (kt_n), to be sent to the appropriate stockpile bin from the current waste tonnes of the grade-tonnage curve. Also, subtract the proportionate amount of $\left(qm - qp\right)$ with grades below g_l to be sent to the waste dump from the current waste tonnes of the grade-tonnage curve.
- Calculate the annual profit for the mining operation by Equation (24)

$$pr_n = \left(\left(\left(sp - sc\right).g_{avg_n}.r_{avg}\right) - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP}\right)qp - \left(mc + bc.R_{OB} + ic.R_{IB}\right)qm \tag{24}$$

- After depletion of pit reserves, start reclaiming stockpile. If total stockpile tonnage is more than QP, repeat the algorithm from step 1 for the cut-off grade optimization of stockpile reclamation; otherwise proceed.
- Calculate the annual profit for stockpile reclamation by Equation (25)

$$pr_n = \left(\left((sp - sc).g_{avg_n}.r_{avg} \right) - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP} \right) qp - (kc) qk \tag{25}$$

7.3) Utilizing the stockpile simultaneously with the mining operation:

- Determine the stockpile duration, kd. For instance, when the stockpile duration is one year, it means any material that enters the stockpile should be used in one year.
- If $q_o \geq QP$
- For the year n set the $qp = QP - kt_{n-kd}$
- Otherwise set $qp = q_o - kt_{n-kd}$
- Calculate the amount to be mined in year n by Equation (22)
- Adjusting the grade-tonnage curve without changing it's shape: subtract the proportionate amount of qp from the ore tonnes and the proportionate amount of $(qm - qp)$ with grades between g_{p_n} and g_l, stockpile tonnes (kt_n), to be sent to the appropriate stockpile bin from the current waste tonnes of the grade-tonnage curve. Also, subtract the proportionate amount of $(qm - qp)$ with grades below g_l to be sent to the waste dump from the current waste tonnes of the grade-tonnage curve.
- Calculate the annual profit for the mining operation and stockpile reclamation by Equation (26)

$$pr_n = \left(\left((sp - sc).g_{avg_n}.r_{avg} \right) - pc - tc.R_{TCS} + bc.R_{OB} + ic.R_{IB} - \frac{F}{QP} \right) (qp + kt_{n-kd}) - (mc + bc.R_{OB} + ic.R_{IB}) qm - (kc).kt_{n-kd} \tag{26}$$

8. If qp is less than processing capacity QP

   Set $T = n$ and go to next step,

   Otherwise set $n = n + 1$ and go to step 3.
9. Calculate the incremental NPV_n from year n to T by using equation (28)

$$NPV_n = \sum_{k=n}^{T} \frac{pr_k}{(1+d)^{k-n+1}} \tag{28}$$

10. If the calculated NPV_1 is not in a specific tolerance from the previous iteration, update the opportunity costs and go to step 1. Otherwise, stop the process, the NPV of the whole deposit is maximized and the g_{p_n} for the years 1 to T (life of mine) is the optimum cut-off grade policy.

7. Case Study

The final pit limit for the case study was generated with Whittle (Gemcom Software International, 2013) software using the LG algorithm (Lerchs and Grossman, 1965). Table 1 shows information about the oil sands deposit for the case study and Table 2 contains economic parameters and operational capacities for our model oil sands mine which is processing limited. The economic data are extracted and compiled based on Ben-Awuah (2013) and Burt et al. (2012). Figure 3 represents the cumulative grade-tonnage distribution of the deposit and Figure 4 shows the bitumen grade distribution in the case study area at level 300m.

Table 1: Oil sands deposit final pit characteristics

Description	Value
Total tonnage of material (Mt)	1340.5
Total ore tonnage (Mt)	452.1
Total TCS dyke material tonnage (Mt)	341.9
Total OB dyke material tonnage (Mt)	426.9
Total IB dyke material tonnage (Mt)	167.8
Total waste tonnage (Mt)	293.7

Table 2: Economic parameters and operational capacities

Parameter (unit)	Value	Parameter (unit)	Value
Mining cost ($/tonne)	2.3	R_{TCS}	0.7563
Processing cost ($/tonne)	5.03	R_{OB}	0.4805
Selling cost ($/bitumen %mass)	0	R_{IB}	0.1889
Stockpiling cost($/tonne)	0.5	Mining capacity (Mt/year)	Unlimited
Selling price ($/bitumen %mass)	4.5	Processing capacity (Mt/year)	40
Annual fixed cost (M$/year)	480	Refinery capacity (Mt/year)	Unlimited
TCS dyke material cost ($/tonne)	0.92	Mining recovery fraction (%)	100
OB dyke material cost ($/tonne)	1.38	Processing weighted average recovery (%)	84
IB dyke material cost ($/tonne)	1.38	Discount rate (%)	15

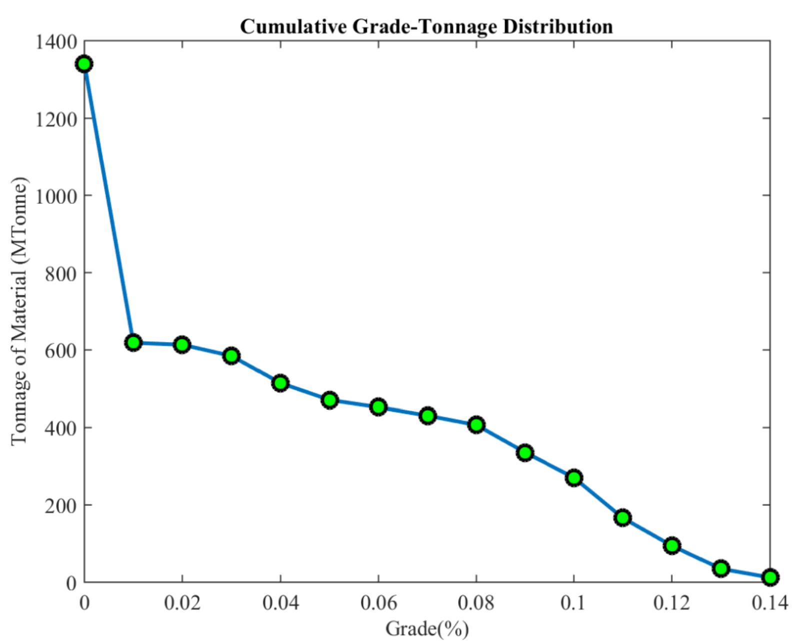

Figure 3 - Cumulative grade-tonnage distribution of the oil sands deposit

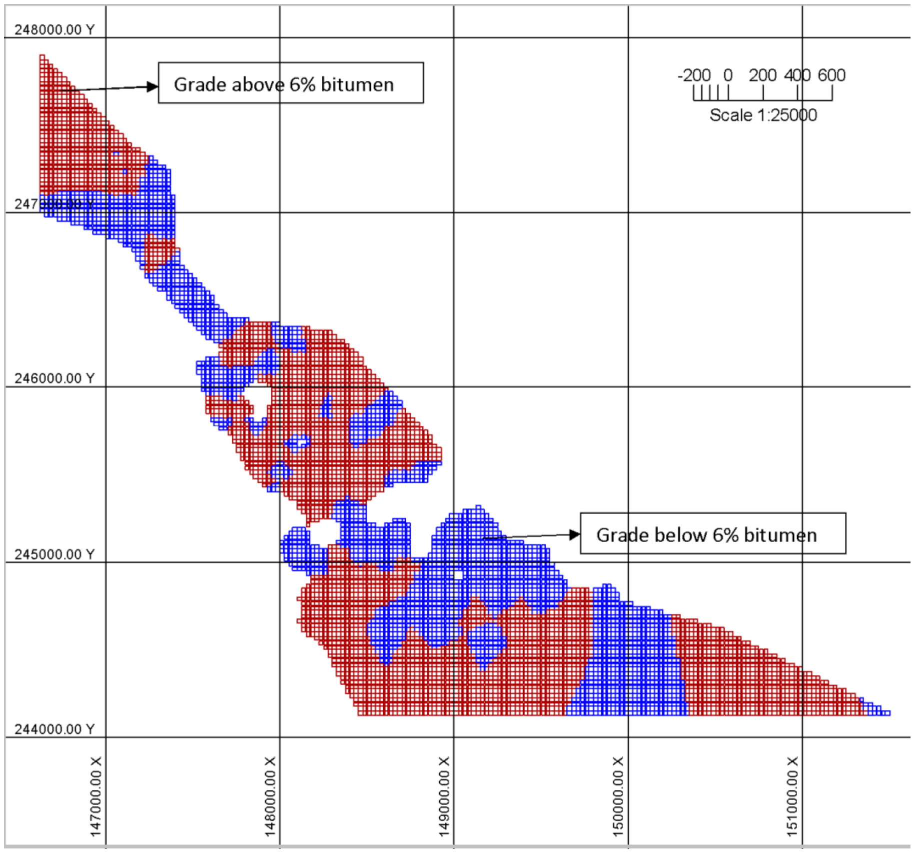

Figure 4 - Bitumen grade distribution in the case study area at level 300m

The ICOGO model was coded in Matlab (Mathworks, 2015) and implemented on the oil sands deposit. The grade-tonnage distribution of the deposit which is needed for the ICOGO model is presented in Table 3. We have implemented the model with three stockpile scenarios: 1) without stockpile, 2) reclaiming stockpile at the end of the mine life and 3) reclaiming stockpile simultaneously with the mining operation. The termination criterion for heuristic optimization algorithm is NPV tolerance of $5M. The results for each of the production schedule scenarios after cut-off grade optimization are presented in

Table 4 to

Table 6, respectively.

Table 3: Grade-Tonnage distribution of the oil sands deposit

Grade (%)	Tonnage (Mt)
0 – 6	888.4
6 – 7	21.2
7 – 8	24.2
8 – 9	70.9
9 – 10	65.2
10 – 11	104.3
11 – 12	71.8

12 – 13	59.8
13 – 14	22.4
Above 14	12.3

Table 4: Production schedule with optimum cut-off grade policy without stockpile

Year	Cut-off grade (%)	Average head grade (%)	Material mined (Mt/year)	Material processed (Mt/year)	Incremental NPVs ($M)
1	6.96	10.56	124.2	40	2539.1
2	6.86	10.54	123.5	40	2433.2
3	6.75	10.52	122.9	40	2312.1
4	6.62	10.50	122.1	40	2173.4
5	6.47	10.47	121.3	40	2015.1
6	6.30	10.43	120.3	40	1833.9
7	6.10	10.39	119.2	40	1627.3
8	6.00	10.37	118.6	40	1391.7
9	6.00	10.37	118.6	40	1121.8
10	6.00	10.37	118.6	40	811.4
11	6.00	10.37	118.6	40	454.5
12	6.00	10.37	12.6	4.2	44.1

Table 5: Production schedule with optimum cut-off grade policy and stockpile reclamation after the mine is exhausted

Year	Cut-off grade (%)	Average head grade (%)	Material mined (Mt/year)	Material to stockpile (Mt/year)	Material from stockpile (Mt/year)	Material processed (Mt/year)	Incremental NPVs ($M)
1	6.96	10.56	124.2	1.9	0	40	2548.2
2	6.86	10.54	123.5	1.7	0	40	2443.5
3	6.75	10.52	122.9	1.4	0	40	2323.9
4	6.62	10.50	122.1	1.2	0	40	2187.1
5	6.47	10.47	121.3	0.9	0	40	2030.9
6	6.30	10.43	120.3	0.6	0	40	1851.9
7	6.10	10.39	119.2	0.2	0	40	1648.1
8	6.00	10.37	118.6	0	0	40	1415.5
9	6.00	10.37	118.6	0	0	40	1149.2
10	6.00	10.37	118.6	0	0	40	842.9
11	6.00	10.37	118.6	0	0	40	490.7
12	6.00	10.37	12.6	0	0	4.2	85.7
13	6.00	6.5	0	0	7.9	7.9	47.9

Table 6: Production schedule with optimum cut-off grade policy and simultaneous stockpile reclamation during mining

Year	Cut-off grade (%)	Average head grade (%)	Material mined (Mt/year)	Material to stockpile (Mt/year)	Material from stockpile (Mt/year)	Material processed (Mt/year)	Incremental NPVs ($M)
1	7.03	10.57	124.6	2.1	0	40	2607.3
2	6.93	10.55	117.7	1.7	2.1	40	2511.4
3	6.80	10.53	117.9	1.4	1.7	40	2380.4
4	6.66	10.50	117.8	1.2	1.4	40	2233.8
5	6.50	10.47	117.7	0.9	1.2	40	2068.6
6	6.31	10.44	117.6	0.5	0.9	40	1883.1
7	6.11	10.40	117.5	0.1	0.5	40	1674.3
8	6.00	10.37	118.1	0	0.1	40	1439.9
9	6.00	10.37	118.6	0	0	40	1175.3
10	6.00	10.37	118.6	0	0	40	872.9
11	6.00	10.37	118.6	0	0	40	525.3
12	6.00	10.37	35.8	0	0	12.1	125.5

7.1. Discussion

In this case study, the mining operation is only limited by the processing capacity. In the first scenario, the total NPV generated including the waste management cost is $2539.1M. The mine operates at the maximum processing capacity until the last year when the material in the final pit limit is finished. Figure 5 shows the schedule for material mined and the amount of produced TCS dyke material. The model generates a uniform production schedule for ore, IB, OB, TCS and waste material over the life of mine.

In the second scenario, the life of mine is increased by one year and the generated NPV shows $9.1M improvement in the total NPV of the operation. This increase results from reclamation of the stockpile after the mining operation. Here, the total amount of ore that has been processed increases by 7.9 Mt compared to the first scenario which sends the 7.9 Mt of material below the optimum cut-off grade to the waste dump. Figure 6 shows the schedule for material mined, reclaimed and the amount of produced TCS dyke material for Scenario 2. Figure 7 shows the amount of material sent to the stockpile.

In oil sands mining, maintaining a uniform average head grade is one of the most important issues. Due to the fact that we only stockpile the low grade ore material, we will miss the opportunity of blending the low grade and high grade materials when we want to reclaim the stockpile material.

Table 5 shows that, when we start reclaiming the stockpile material after the mine is exhausted, the average head grade will have a significant drop which directly reduces the generated profit.

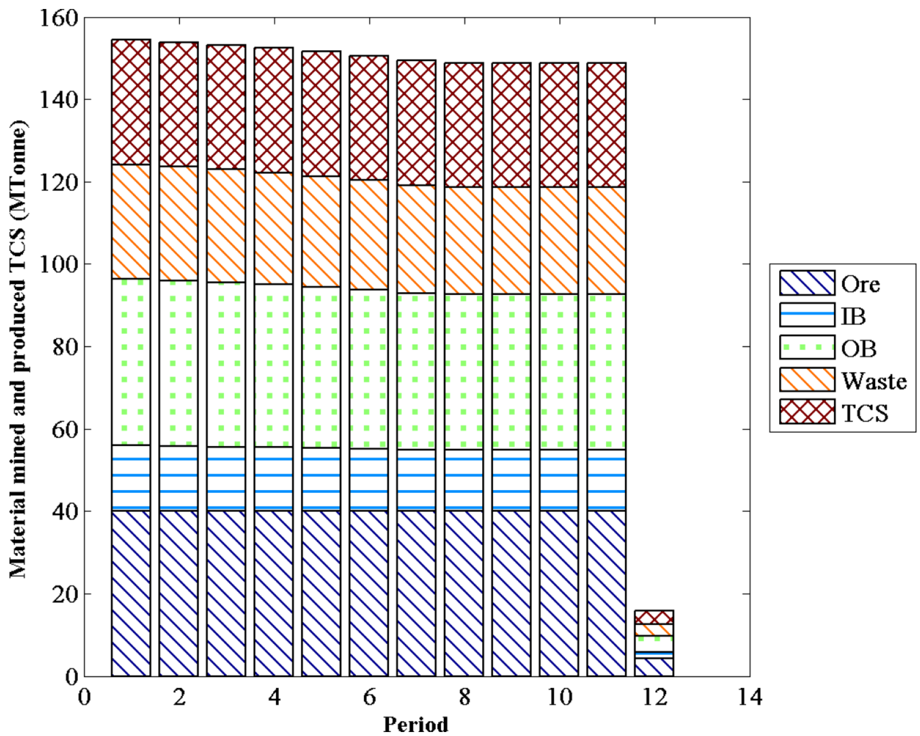

Figure 5 - Scenario 1: Schedule for material mined and produced TCS

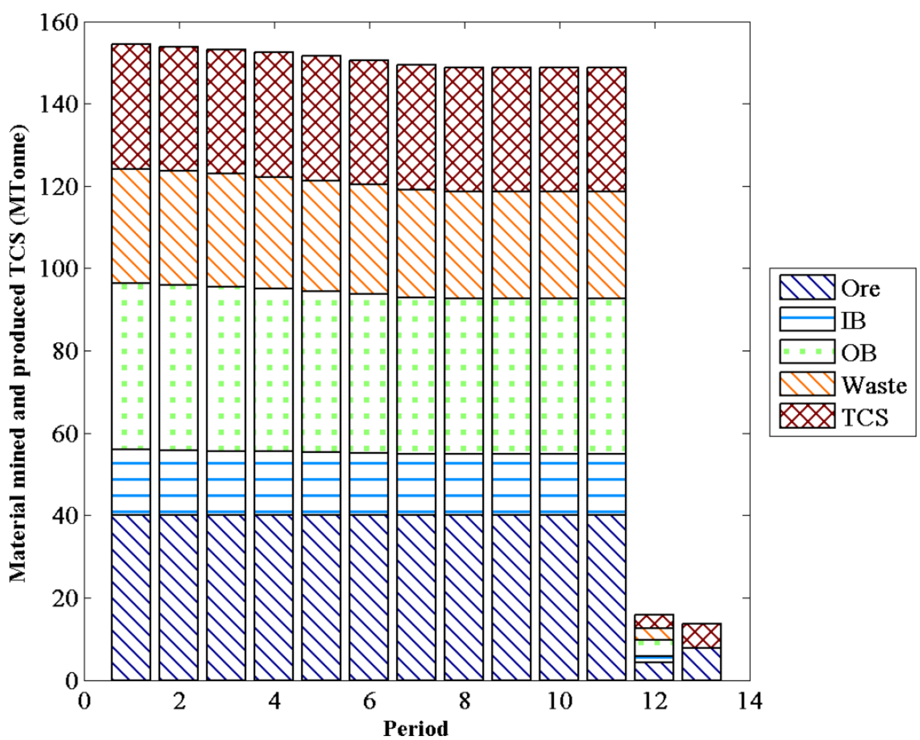

Figure 6 - Scenario 2: Schedule for material mined, reclaimed and produced TCS

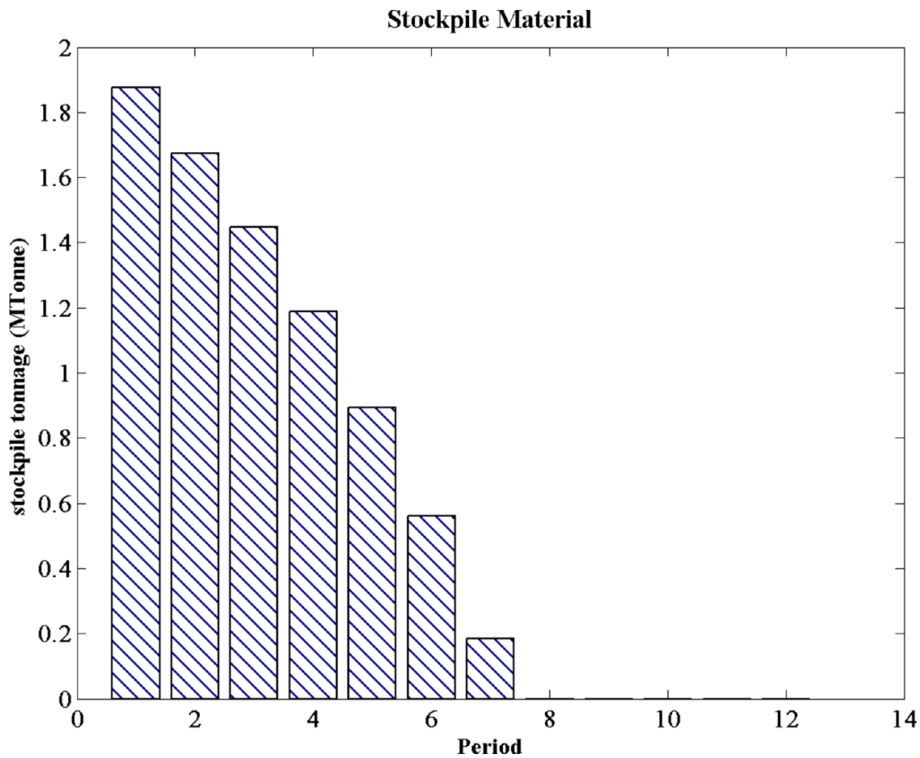

Figure 7 - Scenario 2: Schedule for material stockpiled

In order to prevent this problem, we can utilize the stockpile parallel to the mining operation. Based on material characteristics, any limitations on stockpiling duration such as processing recovery can be determined. In the case of this oil sands mining case study, to prevent oxidation of ore material that affects processing recovery, one year stockpiling duration is chosen. In the third scenario, production schedule with optimum cut-off grade policy and utilization of the stockpile simultaneously with mining operation is presented. In this scenario, the amount of material that is sent to the stockpile in a given year must be used in the following year. Since some portion of processing capacity is filled with the stockpile material, less material above cut-off grade will be mined each time. It can be seen in

Table 4 and

Table 5 that the mining capacity for the first and second scenarios have a decreasing gradient from the first year to the last year due to dynamic nature of optimum cut-off grade policy. However, in the third scenario as a consequence of using the stockpile material during the first 8 years, the mining capacity is less than the other scenarios in those years. Also, after the year 8 the mining capacity is increased since there is no more material from the stockpile. Figure 8 represents the schedule for material mined, reclaimed and the produced TCS dyke material for the third scenario and Figure 9 shows the schedule of material sent to the stockpile.

Utilizing the stockpile material parallel to the mining operation provides blending opportunity and maintains the average head grade for plant feed. The third scenario generated an overall NPV of \$2607.3M. It improved the NPV of the operation by \$68.2M compared to the first scenario and \$59.1M compared to the second scenario.

Figure 10 shows the cut-off grades profile for three scenarios. The first two scenarios have similar cut-off grades, but the second scenario has one more year mine life because of utilization of the stockpile after the mining operation. It should be noted that the stockpiled material can be used in year 12 since the processing capacity is not at the maximum. The third scenario has the highest cut-off grade profile compared to the others.

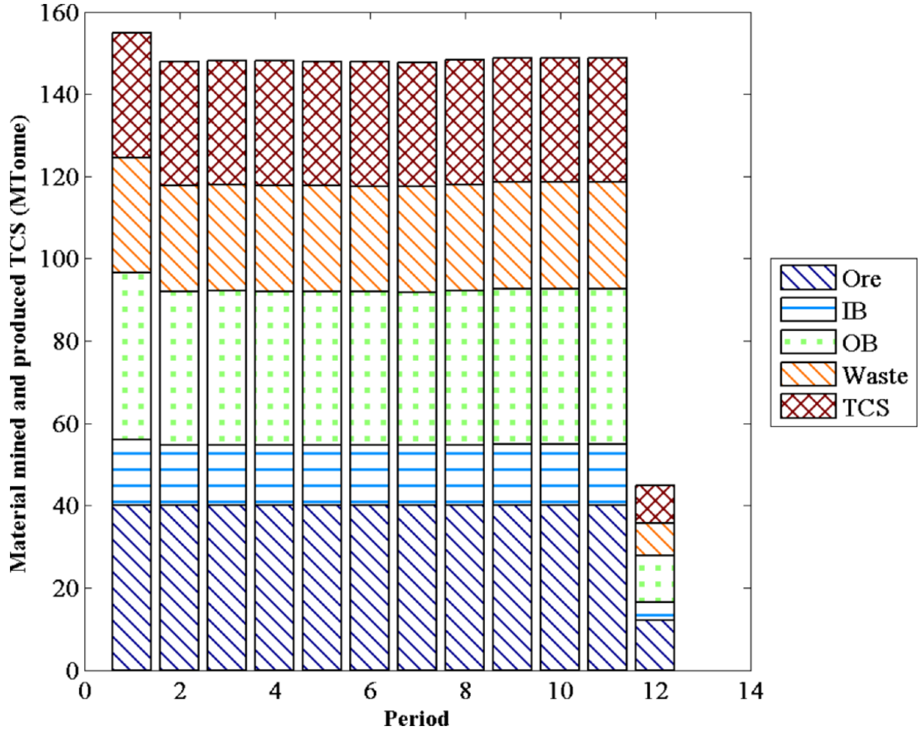

Figure 8 - Scenario 3: Schedule for material mined, reclaimed and produced TCS

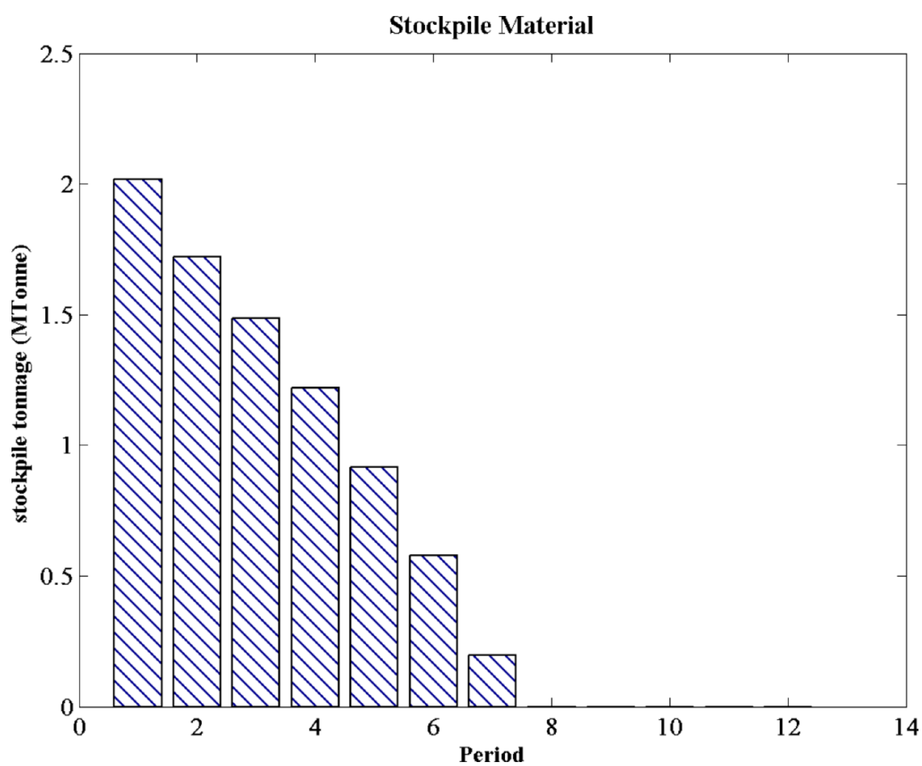

Figure 9 - Scenario 3: Schedule for material stockpiled

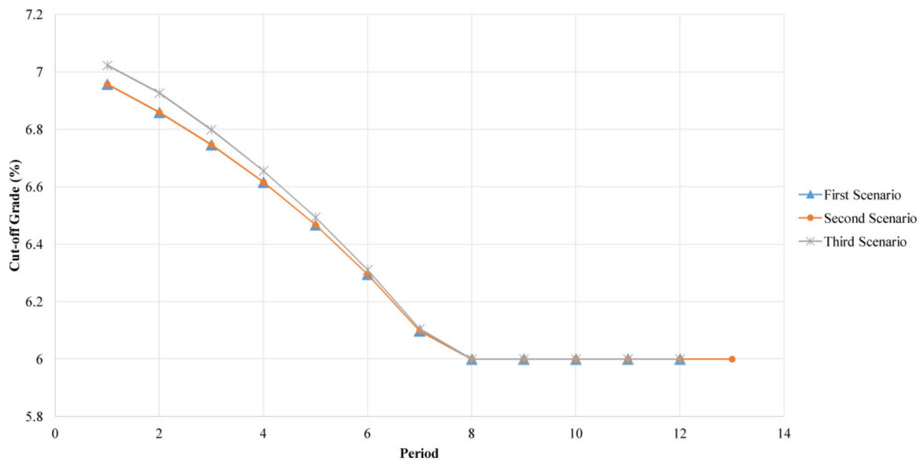

Figure 10 - Cut-off grades profile for the three scenarios

8. Conclusion and Future Work

In this paper, we developed, implemented and tested a cut-off grade optimization model to incorporate waste management cost and limited stockpiling duration for oil sands long-term production scheduling. A real data set of an oil sands deposit was used to verify the model. The model generates an optimum cut-off grade policy and a uniform production schedule for ore, OB, IB, TCS and waste material over the mine life. The OB, IB and TCS dyke material are required for dyke construction. The benefit of using the stockpile with two reclamation methods was presented. Reclaiming the stockpiled material after the mining operation results in increasing the total ore tonnage. Also, utilizing the reclamation of stockpiled material simultaneously with the mining operation increased the total ore tonnage as well as maintaining the average head grade required by the processing plant. By maintaining the average head grade, the total NPV generated in the third scenario was higher than the second scenario.

The optimum cut-off grade policy and the production schedule generated by the ICOGO model can be used as guidance for the input parameters for medium and short-term production scheduling. The authors are developing a comprehensive Mixed Integer Linear Goal Programming (MILGP) model which features mining, processing, stockpiling, IB, OB, TCS and grade goal functions for medium and short-term planning. The initial targets of these goal functions in the MILGP model will be defined based on the results from the ICOGO model.

9. References

[1] Abdollahisharif, J., Bakhtavar, E., and Anemangely, M. (2012). Optimal cut-off grade determination based on variable capacities in open-pit mining. *Journal of the Southern African Institute of Mining and Metallurgy*, *112* (12), 1065-1069.

[2] Ali, M. W. and Khan, M. N. (2004). Management of open pit mining operations with ore stockpiles. *Journal of Engineering and Applied Sciences (Peshawar)*, *23* (1), 51-56.

[3] Asad, M. W. A. (2005). Cutoff grade optimization algorithm with stockpiling option for open pit mining operations of two economic minerals. *International Journal of Surface Mining, Reclamation and Environment*, *19* (3), 176-187.

[4] Asad, M. W. A. (2007). Optimum cut-off grade policy for open pit mining operations through net present value algorithm considering metal price and cost escalation. *Engineering Computations*, *24* (7), 723-36.

[5] Asad, M. W. A., Qureshi, M. A., and Jang, H. (2016). A review of cut-off grade policy models for open pit mining operations. *Resources Policy*, *49* 142-152.

[6] Asad, M. W. A. and Topal, E. (2011). Net present value maximization model for optimum cut-off grade policy of open pit mining operations. *Journal of the Southern African Institute of Mining and Metallurgy*, *111* (11), 741-750.

[7] Askari-Nasab, H., Pourrahimian, Y., Ben-Awuah, E., and Kalantari, S. (2011). Mixed integer linear programming formulations for open pit production scheduling. *Journal of Mining Science*, *47* (3), 338-359.

[8] Bascetin, A. and Nieto, A. (2007). Determination of optimal cut-off grade policy to optimize NPV using a new approach with optimization factor. *Journal of the Southern African Institute of Mining and Metallurgy*, *107* (2), 87-94.

[9] Ben-Awuah, E. (2013). Oil sands mine planning and waste management using goal programming.Thesis, University of Alberta, Edmonton,

[10] Ben-Awuah, E. and Askari-Nasab, H. (2011). Oil sands mine planning and waste management using mixed integer goal programming. *International Journal of Mining, Reclamation and Environment*, *25* (3), 226-247.

[11] Ben-Awuah, E. and Askari-Nasab, H. (2013). Incorporating waste management into oil sandslong term production planning. *Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology*, *122* (1), 33-45.

[12] Ben-Awuah, E., Askari-Nasab, H., and Awuah-Offei, K. (2012). Production scheduling and waste disposal planning for oil sands mining using goal programming. *Journal of Environmental Informatics*, *20* (1), 20-33.

[13] Burt, M., Crawford, T., and Arcand, A. (2012). Fuel for Thought: The Economic Benefits of Oil Sands Investment for Canada's Regions. *The Conference Board of Canada*, *Report October 2012*

[14] Dadgelen, K. (1992). *Cut-off grade optimization*. in Proceedings of Proceedings of the 23rd International Symposium on the Application of Computers and Operations Research in the Minerals Industries (APCOM1992) C1 - 157-165,

[15] Dadgelen, K. (1993). *An NPV optimization algorithm for open pit mine design*. in Proceedings of Proceedings of the 24th International Symposium on the Application of Computers and Operations Research in the Minerals Industries (APCOM1993), pp. 257-263.

[16] Ellis, J. (2016). *Directive 082.* Alberta Energy Regulator, Calgary,

[17] Gemcom Software, I. (2013). Whittle strategic mine planning software. Ver. 4.5.5,

[18] Gholamnejad, J. (2008). Determination of the Optimum Cutoff Grade Considering Environmental Cost. *J. Int. Environmental Application & Science*, *3* (3), 186-194.

[19] Gholamnejad, J. (2009). Incorporation of rehabilitation cost into the optimum cut-off grade determination. *Journal of the Southern African Institute of Mining and Metallurgy*, *109* (2), 89-94.

[20] Hall, B. (2014). *Cut-off Grades and Optimising the Strategic Mine Plan.* The Australian Institute of Mining and Metallurgy, Australia, Pages 300.

[21] King, B. (1999). *Cash flow grades*. in Proceedings of Proceedings of the Strategic Mine Planning Conference C1 - Perth, Australia, pp. 1-8.

[22] Lane, K. F. (1964). Choosing The Optimum Cut-off Grade. *Colorado School of Mines Quarterly*, *59* (4), 811-829.

[23] Lane, K. F. (1984). *Cut-off grades for two minerals*. in Proceedings of Proceedings of the 18th International Symposium on the Application of Computers and Operations Research in the Minerals Industries (APCOM1984) C1 - London, pp. 485-492.

[24] Lane, K. F. (1988). *The Economic Definition Of Ore: Cut-off Grades in Theory and Practice.* Mining Journal Books, London,

[25] Lane, K. F. (1997). *The Economic Definition Of Ore: Cut-off Grades in Theory and Practice.* Mining Journal Books, London,

[26] Lerchs, H. and Grossman, I. F. (1965). *Optimum design of open-pit mines*. in Proceedings of Transactions of the Canadian Mining and Metallurgical Bulletin,, pp. 17-24.

[27] Masliyah, J. (2010). *Fundamentals of Oi lsands Extraction.* University of Alberta, Edmonton,

[28] Mathworks, I. (2015). MATLAB Software. Ver. 8.5 (R2015a),

[29] Mol, O. and Gillies, A. C. A. I. o. M. a. M. (1984). *Cut-off grade determination for mines producing direct-shipping iron ore*. in Proceedings of Australasian Institute of Mining and Metallurgy, pp. 283-287.

[30] Mortimer, G. J. (1950). Grade control. *Transactions of the Institution of Mining and Metallurgy*, *59* 1-43.

[31] Nieto, A. and Bascetin, A. (2006). Mining cutoff grade strategy to optimise npv based on multiyear grg iterative factor. *Mining Technology*, *115* (2), 59-64.

[32] Osanloo, M., Rashidinejad, F., and Rezai, B. (2008). Incorporating environmental issues into optimum cut-off grades modeling at porphyry copper deposits. *Resources Policy*, *33* (4), 222-229.

[33] Poniewierski, J. and Hall, B. (2016). Break-even is broken. *AusIMM Bulletin*, (Jun 2016), 68.

[34] Shishvan, M. S. and Sattarvand, J. (2015). Long term production planning of open pit mines by ant colony optimization. *European Journal of Operational Research*, *240* (3), 825-836.

[35] SME (2011). Systems Engineering. in *Mining Engineering Hand Book*, Vol. 1, 3 ed, pp. 839-853.

[36] Tabesh, M. and Askari-Nasab, H. (2011). Two-stage clustering algorithm for block aggregation in open pit mines. *Mining Technology*, *120* (3), 158-169.

[37] Taylor, H. K. (1972). General background theory of cutoff grades. *Transactions of the Institution of Mining and Metallurgy*, *81* 160-179.

[38] Whittle, J. (1999). *A decade of open pit mine planning and optimization - The craft of turning algorithms into packages*. in Proceedings of Proceedings of APCOM'99: Computer Applications in the Minerals Industries: 28 International Symposium C1 - Golden, Colorado, Colorado School of Mine, pp. 15-24.

Management of Mineralized Mine Waste as a Future Resource

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Abstract

After mining completion, the lasting effects of mine waste from the operation are all that is left. Mine waste has negative influences on the environment, prominently due to acid-mine drainage. Currently, even though most natural resources are non-renewable, the majority of mineral resources are not mined until physical depletion, but rather current economic depletion resulting in valuable minerals left behind. With proper attention to waste management planning, the potential to increase the future profits and sustainability of the mine become available. By reprocessing the mineralized waste when metal prices fluctuate favourably, less metal will be left behind. Mineralized waste processing however has limitations. The increase in mineralized waste processability has to be assessed to be able to consider it as potential future resource. Multiple scenarios varying from conventional mining and processing practices to methods involving extensive waste management plans to prepare for future mineralized waste reprocessing are discussed in this research. The paper establishes the practicality of an effective and extensive waste management system and its benefits in life-of-mine planning particularly for non-renewable natural resources.

1. Introduction

Ever since commodities have become a form of currency, whether just for trade or for sale, the convention has been if it cannot be grown, it has to be mined. This idea has remained true, but it also has severe drawbacks, most notably the finite mineral reserves on the planet. This also leads to another issue in the mining industry, which is the convention in which mining takes place. The convention since the beginning of mining has been to mine the easiest, most profitable minerals first, leaving the either lower grade or more difficult minerals to mine for future generations. This convention will require change if the mining industry will continue to prosper.

In more recent history, reprocessing and recycling have started to come into favour, most notably on the higher grade mineralized waste of the past which requires less efficient mining activities (Lottermoser, 2011). This is the beginning of the change to stop the old convention of mining the easiest and most profitable resources first, but rather begin to physically deplete instead of just economically depleting the mineral reserves that have already been tapped into.

This paper looks to identify the issues associated with the current mining practices and waste management systems through an extensive literature review to propose a new system, perform a case study utilizing Geovia GEMS and Whittle (GEOVIA-Dassault., 2014, 2015) and discuss the results alongside any future work and recommendations. The literature review conducted for the purpose of this paper was done on two major categories. One section is regarding what needs to be addressed in today’s mining conventions. The second section focuses on the proposed changes that could be made to aid in the remedy of these scenarios. The sections are separated further in the literature review to include gold recovery, processing, resource depletion, mine sustainability and environmental impacts. A proposed framework has been established and a case study utilizing a known gold deposit will be conducted utilizing Geovia GEMS (GEOVIA-Dassault., 2014), Geovia Whittle (GEOVIA-Dassault., 2015) in tandem with the newly proposed framework to establish the potential benefits associated with a proper mineralized waste management system.

The paper is organized into six (6) sections that are all utilized in unison to convey the necessity for change in the current practices of mineralized waste management. Section 1 is the introduction; Section 2 is the literature review that was conducted; Section 3 is the proposed conceptual frameworks to be put into the case study; Section 4 is the cost and revenue forecasted data that will be coupled with the frameworks in a case study to establish the new proposed systems; Section 5 is the discussion of the results; and Section 6 is the conclusions and recommendations of the work that has been completed. This paper does not contain the case study. The case study is still currently being completed using the principals and data presented in this report alongside a set of data for a known gold deposit.

1.1. Problem definition

In mining operations around the world there is what is known as the “cut-off grade”. This is the minimum mineral content within the rock to be mined that allows the mine to operate at a profit. Currently, this means that mines will not process the mineralized rock that has been extracted with a grade lower than the “cut-off grade” and will also make attempts in design and operation to reduce the amount of rock extracted below that “cut-off grade” by leaving them in-situ.

This leads to various sustainability issues in the mining industry, led by the lack of physical depletion of the mineralized zones of rock. By only mining what is currently economical, it results in large quantities of mineralized rock left behind. For natural resources that are essentially non-renewable, this approach needs to be re-evaluated.

This research looks to evaluate different approaches to waste management with the view of considering mineralized mine waste as a future potential resource for reprocessing and implement complex systems for the management of the mineralized waste in order to use the current waste as a future resource.

1.2. Aims and objectives

The aims of this research are to improve mine sustainability by the management of mineralized mine waste and determine the impacts of mineralized waste management as a future resource through four core objectives. These objectives are:

- Analyzing and understanding the current mining and waste management practices used in the mining industry
- Proposing and implementing a conceptual framework for a waste management system that enables reprocessing of mineralized waste directly by the plant.
- Discussions and legislative recommendations for life of mine waste management systems for non-renewable natural resources.

1.3. Research and analysis methods used

In the analysis of mineralized waste management as a future resource, various techniques for evaluation are needed to confirm or refute the idea. The first technique used was a comprehensive literature review on current mining and waste management practices which are mainly based on economic depletion frameworks. Following the literature review, the research focused on using historical economic and processing data to forecast well into the future in order to examine the future aspect of the problem definition. Finally, a case study using the forecasted data and a proposed waste management strategy were simulated to establish and compare the impact of the implemented waste management systems to reprocess the mineralized waste in the future. The case study was based on a gold reserve using Geovia GEMS and Whittle (GEOVIA-Dassault., 2014, 2015).

2. Literature Review

2.1. Current mining practices

The mining industry is a vital part of the global economy as well as global technological advancements. The dependence on mining to produce large amount of both metals and non-metal to meet current needs have resulted in the processing of high volumes of mineralized materials and subsequently producing huge amount of waste (Lottermoser, 2010).

In the mining industry, not all mineralized rock is economical to extract and process under the current economic and technological conditions. This does not mean the material is worthless but can still be rich in minerals. Due to unfavourable economic conditions, processing and extraction technology limitations, full extraction of the resources from the mineralized materials may not be possible. Past processes with less efficient extraction and processing techniques have resulted in wastes with high mineral content still within them (Lottermoser, 2010).

The term "mine waste" is used to categorize the material that is extracted from the ground with no current economic value, and is thus stored or discarded rather than processed (Lottermoser, 2010). Mining operations produces large amounts of waste, be it waste rock from the extraction of mineralized rock to tailings from the processing and extraction of metals from the rock. The impoundments required to contain the waste materials often take a very large geographic footprint. These containment facilities are amongst the largest facilities used in any industry. Because of this, the long-term impacts of the waste facilities and the disposal of waste require extra attention in the design phase and in the mining operations bearing in mind that the extent of hydrological systems in waste storages are not fully understood and must be used with caution (Mining Minerals and Sustainable Development, 2002). Figure 1 is a visual representation of waste management in current mining practice. It can be seen that the waste dumps and tailings impoundments do not have a sealed base which could allow for future reprocessing of mine waste (Dold, 2008).

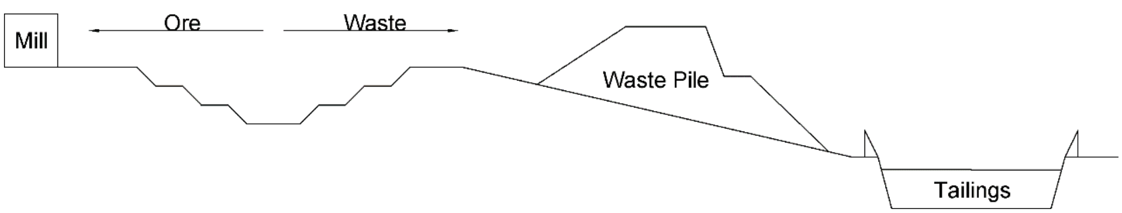

Figure 1: Current mining and processing practices scheme modified from (Dold, 2008)

In mining, technology has and still is a vital part of the industry. In order to both extract and process the minerals in the mining cycle, technology leads the way in the potential to do so. Though this is certainly the case, technology in mining evolved slowly leading up to the Industrial Revolution, at which point the need for better extraction of resources became necessity. This necessity led to the development of numerous technologies that are still essential in mining processes today, such as: flotation, new methods of pyrometallurgy, geophysics, drilling practices and machinery (Giurco et al., 2010). Improved extraction techniques and technologies have kept the relative metal prices of these metals moderately constant for over 50 years (Gordon et al., 2006). Exploration drilling technology is another major area for potential future advances. The oil industry is a major contributor in the need for faster and more efficient drilling technology. Their need for lower cost and better exploration practices drives the research in drilling technologies. 'Hot dry rock' geothermal energy production, which requires deep drilling technology to reach the hot granites at three to four kilometers below surface, has come to the forefront of energy production due to the increased drilling capabilities emanating from technological advancement. Given the need to drill deeper for future mineral discoveries and current mineral production, drilling technology advancements will continue to take a leading role in mining industry and future research prospects (Giurco et al., 2010).

The mine waste hierarchy in Figure 2 is a well-established guide for prioritizing waste management practices, showing most favoured at the top to least favoured at the bottom. As seen, minimization of creation of mine waste is of course the preferred option, whereas disposal and treatment being the least preferred option. Reuse and recycling is amongst the top feasible options in waste management (Lottermoser, 2011). However, most common practice used in conventional mining is the treatment, disposal and storage, the least favoured option.

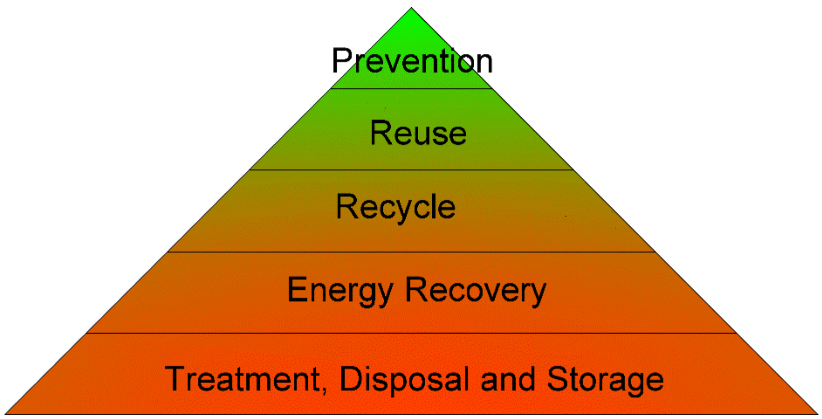

Figure 2 : Mine waste hierarchy modified from (Lottermoser, 2011)

2.2. Proposed mining practices

Not only are extraction technologies vital in mining, but the processing and refining processes are also of critical importance. This means that the future research associated with the processing and refining processes will continue to be in the forefront of the research efforts due to the declining ore grades and more complex ore compositions (easier and higher grade ores have been mined first, leaving the harder and lower grade ores behind) (Giurco et al., 2010).Technological advancements in the mining industry, processes that improve economic value of minerals (through better separation or likewise) and improved milling and refining processes will increase the potential extraction of minerals in mining operations and will prove to be essential in future processing (Hatayama et al., 2014).

In the mining industry, the waste is typically mineralized materials that are not economical to process at the time of extraction or the waste effluent that is a byproduct of the processing and refining of the materials. The economic conditions are a major contributing factor as to whether or not the material is economically viable for processing at the time of extraction. Another major factor for mineralized materials being left behind in the waste stream is processing and refining inefficiencies. These factors, amongst some others, result in the mineral reserve not reaching complete extraction, and waste streams with mineralized materials still being left behind (Lottermoser, 2010). Mine waste may not necessarily be completely worthless, but rather not economically valuable under the current economic or technological conditions. These materials often contained valuable mineralization that can be used as a future resource. As economic and technologies change, materials that were previously considered to be waste are now commodities in the new market. Furthermore, as the commodity demand and price increase, the need for the new technologies and reprocessing increases, resulting in further research efforts on the subject. Current waste can be used as a future resource in times of commodity scarcity (Lottermoser, 2011).

Figure 3 and Figure 4 show a proposed mineralized waste management system along with the mine sustainability and profits versus the life of investment graph for the corresponding system respectively (Dold, 2008).

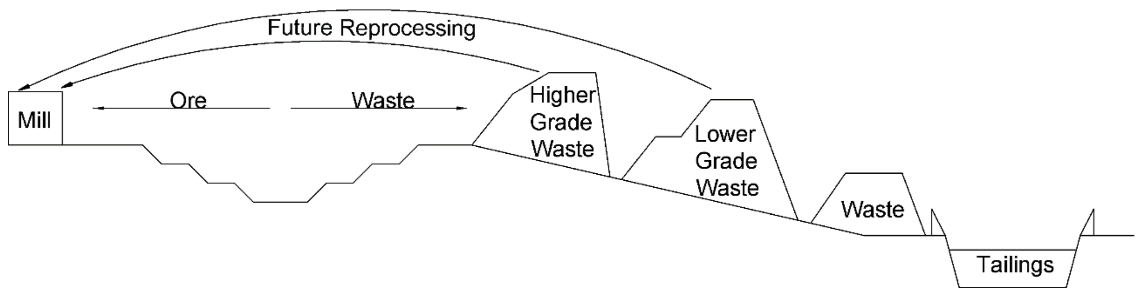

Figure 3 : Proposed waste management scheme for future reprocessing of mineralized wastes modified from (Dold, 2008)

Figure 4 is a simplified schematic of the return on investment as mine life increase due to the implementation of the waste management system as compared to the associated ore grades within the operation. This shows the additional profits for utilizing the proposed reprocessing practices and mine life, these are in addition to the profits made by utilizing the higher grade profit margins previously.

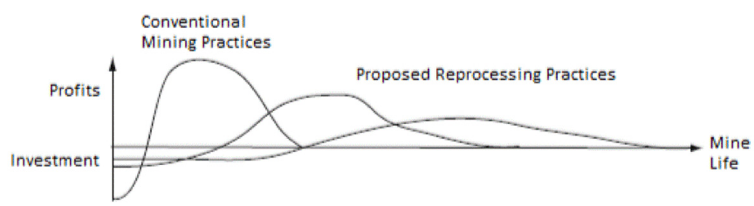

Figure 4 : Visual representation of value of proposed waste management system modified from (Dold, 2008)

The reprocessing and recycling, as well as miscellaneous reuse of the mine wastes is done for both financial return as well as the practical uses (ie. fill for roads, etc.). With the increasing demand for minerals and materials in the global market, the recovery of the valuable minerals and reuse of the wastes is becoming increasingly important and enticing (Lottermoser, 2011). Recycling and reprocessing mine wastes and effluents is done to recover the valuable minerals and metals that are leftover in the waste. This is done due to improved economic conditions or technologies in the reprocessing and refining stages, as well as potentially improved extraction methods or technologies (Lottermoser, 2011).When recycling and reprocessing mineralized wastes, the overall cost depends on various factors. The approach in modern mining has been trending toward recycling and reprocessing of mine wastes. This is becoming more possible, especially when reprocessing older mine wastes that are higher in mineralization because of improved processing and refining technologies as well as increased metal demands (Lottermoser, 2011).

Since operational decisions are often expensive to reverse, if reversible at all, it is best to make these decisions in the planning phases. These decisions range from mining method to waste management plans. This enables further decisions to have a directive, ensuring that the future decisions are supported by the intended final outcome. Mine closure plans typically only focus on the environmental aspects of closure and its impacts on the surrounding ecosystems. Integrating social and economic impacts as well is important as well to maintain sustainable mining operations (Mining Minerals and Sustainable Development, 2002).

The mining industry however is slow to change, and should focus its research on the advancement of technologies and processes that cause positive changes in the conventional mine cycles, and thus increased mine life. These advancements should not cause an increased negative social or environmental impact as a result of the mining operations as a consequence of the new technologies or practices (Prior et al., 2012).

2.3. Gold recovery and processing

As innovation continues in the mining industry, a major advancement in the gold recovery process was the implementation was heap leaching. This is done by placing the ore in large piles or "heaps" and having the solution, typically cyanide, sprayed over the piles. This causes the solution to dissolve and carry the metals from the piles of ore which can later be captured and further processed to obtain the metals. This method is now widely used in lower grade ores, most notably in gold and copper mines (Giurco et al., 2010). The recovery process in gold production is a two - staged hydrometallurgical process. The gold is first dissolved from the ore in a cyanide solution that is collected afterwards. The second stage is the recovery phase in which the gold is recovered from the solution using various techniques, typically zinc cementation or carbon adsorption (Lottermoser, 2010). Cyanide is a chemical compound used in mineral processing, typically for gold (and silver). The compound is created when carbon and nitrogen combine to form (CN^-). Cyanide is used in a process known as leaching, in which it dissolves the metals from the ore to be later recovered. This is one of the most common processed used in the mining industry to recover gold from the ores (Lottermoser, 2010).

2.4. Resource depletion

Resources that are obtained through mining are non-renewable and thus finite resources. These resources will eventually become depleted as mining operations continue and commodity needs rise. The current issue however, is the fact that reserves are not being mined to depletion in terms of the mineral resource, but rather to an economic depletion (Giurco et al., 2010). Currently, physical depletion of minerals in the mining industry does not represent a non-availability of a resource, but rather economic depletion coupled with social and environmental constraints and impacts that determine which mineral reserves are extracted (Willett, 2002; Giurco et al., 2010).

The debate of mineral depletion is not around whether or not depletion is occurring; this is well known. The debate amongst researchers is the mechanism of depletion, either physical depletion or otherwise (Gordon et al., 2006; Tilton and Lagos, 2007; Giurco et al., 2010). The debate regarding mechanisms are fueled by the question if the increase in commodity price and/or technology advancements (Giurco et al., 2010) will allow previously waste materials to be considered as resources (Willett, 2002; Prior et al., 2012). Tilton and Lagos (2007) maintain the stance that following the fixed stock paradigm is not representative of the actual availability of resources (that resources on the plant are finite); instead that an opportunity-cost paradigm is more representative of actual resource availability (usable and retrievable resource quantity with associated opportunity costs).

The "Prophesies of Scarcity" written by Williamson (1945) suggests that there is a response to the depletion of both renewable and non-renewable resources. He proposes that resource depletion models are queues that resource management should be more integral in planning phases (Giurco et al., 2010). Though this concept has mostly been researched in fields of renewable resources (fisheries, forestry, etc.), similar concepts can be discussed to some extent, with further research certainly focused on the non-renewable resources required (Giurco et al., 2010).

Based on the expectation that the mining industry will continue to advance technologically and in new techniques the efforts that were previously focused on resource depletion analysis has been hindered in the last twenty years (Giurco et al., 2010). Another issue on the horizon is the fact that as resources are becoming more available globally due to the mining industry's rapid expansion across many countries; the physical depletion of mineral resources has effectively been ignored for economical depletion instead, causing future resource considerations to be forgotten in the process (Tilton, 1996; Willett, 2002; Giurco et al., 2010). The fact that mining rates have continually increased means that eventually mineral reserves will become exhausted (Giurco et al., 2010; Prior et al., 2012).

2.5. Mine sustainability

Though progress in terms of technology and awareness as well as practices has improved in the past 30 years, the course in which correction had to be made has not been followed. Based on the rate at which resources are being consumed, the world will require more resources than available on earth in the 21st century (Meadows et al., 2005). This graph (Figure 5) shows the number of Earths required to provide the resources used by humanity and to absorb their emissions for each year since 1960, and as seen the trend continues upwards (Meadows et al., 2005). Between 1975 and 1980, humanity exceeded the capacity for the earth to sustain the activities, requiring change in practices to being to remedy the situation.

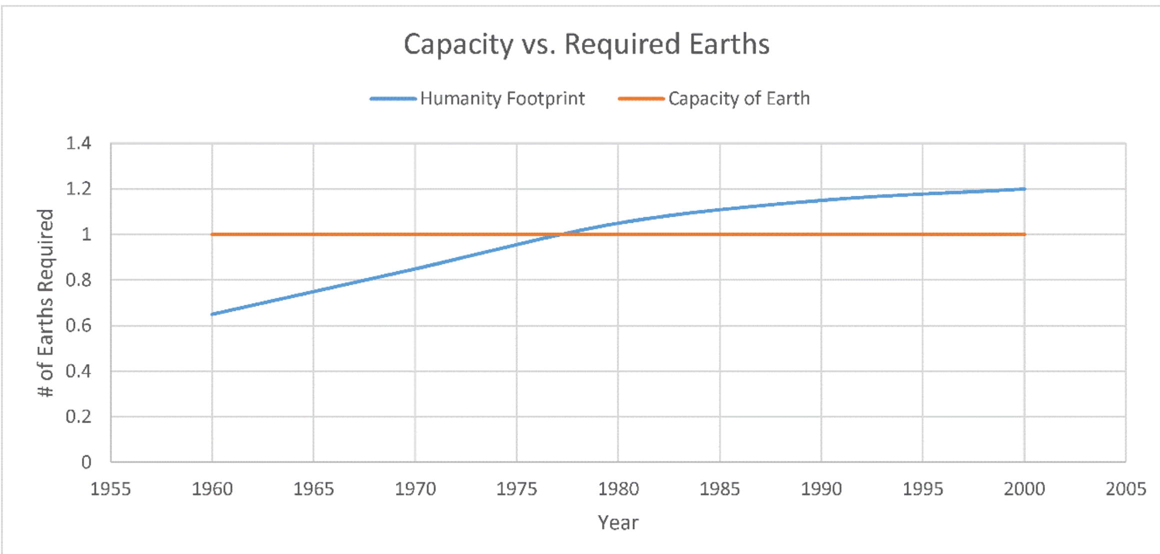

Figure 5 : footprint vs. earths required for sustainability modified from (Meadows et al., 2005)

Mineral resources will eventually become depleted within the lithosphere, leaving alternate means of production as a necessity. Since mining operations are ongoing still, a future management strategy for metal production will rise in research efforts. Physical depletion is not common in mining practices, but environmental and economic impacts cause viability of reserves to be questioned and sustainable techniques required (Prior et al., 2012).

The peak mineral phenomenon is driven by declining ore grades. This means "the concentration of a particular mineral or metal(s) being mined, as well as the quality of the ore with respect to processing (e.g. fine or coarse grained ore, mineralogy, impurities such as arsenic or mercury, etc)" (Prior et al., 2012) is declining.

In terms of sustainability it is not only the exhaustion of minerals that is of concern, but the shift from the convention of mining and processing the cheaper and higher grade ores prior to the "peak" of the reserves to the more expensive and lower grade ores after the "peak" of the reserves (Prior et al., 2012). In terms of resource sustainability, it has been argued that it is better to continue to mine from existing mines for as long as possible before opening new mines, so long that the mining operation is still operating under productive and economic viability within the sustainability dimension (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 try to start remedying the situation, research into waste recycling is rising in importance (Lottermoser, 2011).

"Sustainability does not mean zero growth" (Meadows et al., 2005). This is referring to the fact that sustainable development has an interest in multiple areas of expansions, not exclusively physical expansion.

2.6. Environmental impacts

Mining requires the extraction of mineral reserves from the earth's lithosphere. This means that in order to mine the valuable materials, waste material is required to be taken out as well in the process. The goal in seeking sustainable mining operations is to minimize the waste taken out of the earth and stored in facilities (Dold, 2008). By its very nature, mining has been and will continue to be a destructive activity that leads to negative environmental impacts. The idea of sustainable mining practices and technologies is to maintain and improve extraction of metals from the ore and increase the economic benefits, while still reducing the negative environmental footprint and minimizing reclamation requirements (Dold, 2008). During mining and processing phase of mineral exploitation, the natural environment is subjected to high rate of depletion. The From production, waste rock are extracted and left in storage areas, whereas the processing and refining produces gangue known as "tailings" that is also stored in impoundments. These "waste" materials may still contain minerals that were uneconomical at the time of extract to process or leftover due to refining and processing inefficiency. This means that not all the minerals extracted from the reserve make it to the refining process, wasting some of the valuable commodities.

As a result of the above circumstance, it is very common to have large volumes of waste rock piles without an adequate records of their physical, chemical and geological properties.. These wastes can contain minerals and materials that cause adverse effects on the surrounding environment and ecosystems (Giurco et al., 2010; Prior et al., 2012).When rehabilitation is done on mining operations, which includes the issues of tailings as well as drainage (notably acid mine drainage), the rehabilitation is constrained by the available technology in both the planning and closure phases of the operation.

The rehabilitation and reclamation of mine sites involves returning the wastes (waste rock typically) to their original location (fill the voids where possible) to allow the mine site to be used for future endeavors. Similar to the mine waste hierarchy, the mine site rehabilitation hierarchy (Figure 6) is a guide for prioritizing rehabilitation strategies and planning strategies for mining operations, identifying the preferred option at the top to the least preferred at the bottom (Lottermoser, 2011).

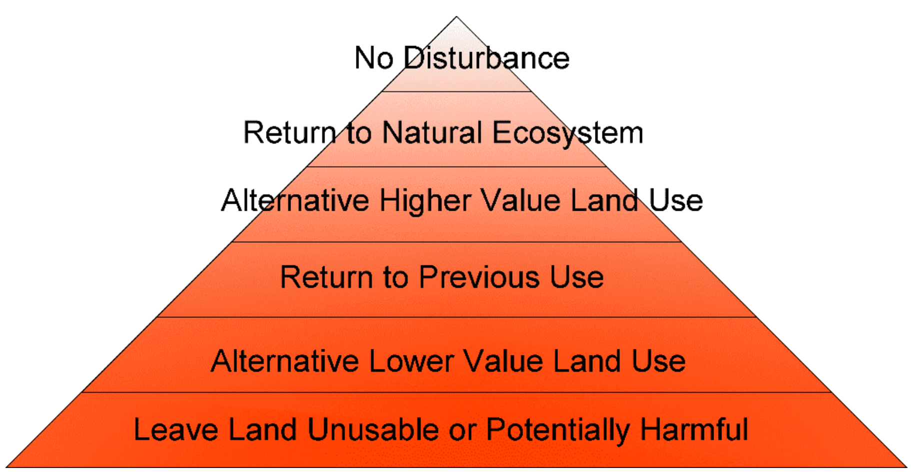

Figure 6 : Rehabilitation and reclamation hierarchy modified from (Lottermoser, 2011)

The global mining industry require companies that wish to start mining operations to undergo an environmental impact assessment prior to work being done on development of the operation. This causes the companies to identify and understand the potential environmental detriments of various aspects of the operation and allows them to attempt to minimize these activities (Lottermoser, 2010).

An example of negative impacts on the environment due to mining operations is in South Africa, the over 1100 operating mines contribute over 72% of the total solid waste stream for the country. This attributes nearly 25000 hectares of land used as waste disposal facilities, mostly in the form of tailings impoundments (Maboeta and van Rensburg, 2003; Lottermoser, 2010).

3. Conceptual Framework

By modeling various scenarios and evaluating those using real data alongside forecasted values, the argument for proper waste management systems will be made with the aim of increasing the amount of mineralized zones that reach physical depletion. The framework in Figure 7 below is used to develop the case studies for which data can be attributed and simulated to determine the practicability of such extensive waste management systems. Figure 7 also shows the impact on the mine life if reclaimable mine waste management systems is used to allow the future reprocessing of mineralized wastes.

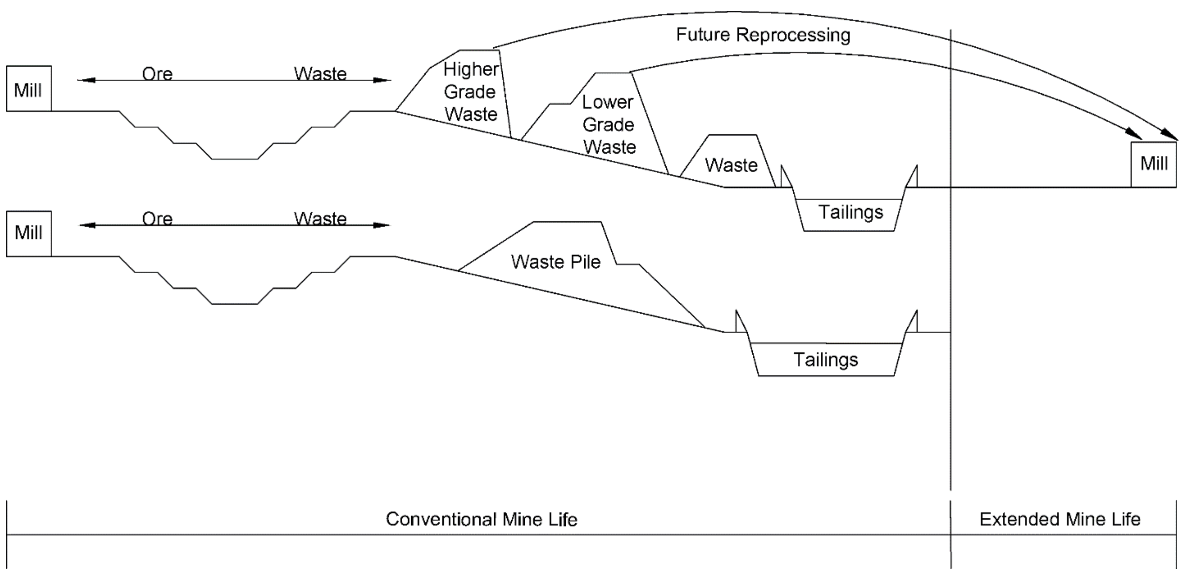

Figure 7 : Mine life impact of sustainable waste management systems

3.1. Current mining practice

The data obtained will be modeled following current mining and waste management practices which is based on economic depletion. The current price of the mineral, mining and processing cost as well as metallurgical recovery will be used in the revenue and profit calculations. This scenario will be the benchmark case in which the simulated models are compared against to establish the feasibility of the proposed waste management systems. Figure 1 shows the conventional method of mining and dealing with the waste produced from the operations based on economic depletion.

3.2. Proposed mining practices

Figure 3 shows the framework used to model three scenarios in terms of mine waste management and future reprocessing of mineralized mine wastes. The scenarios are: 1) Forecasted increased mineral price with reclaimable mineralized waste management system (economic depletion); 2) Future technology advances with reclaimable mineralized waste management system (physical depletion); and 3) combined future technology advances and forecasted increased mineral price with reclaimable mineralized waste management system.

The economic data obtained from the literature review on historical and current mining and milling practices is modeled and used as a basis for mineral price forecasting. This will be implemented using the proposed reclaimable mineralized waste management system. This system tracks the waste grades and separate the waste material into three separate stockpiles: higher grade mineralized waste, lower grade mineralized waste and complete waste (no mineralization). The initial mining operation will be done using current mineral pricing and costs as well as processing practices. These values will be used throughout the three proposed scenarios.

3.2.1. Forecasted increased mineral price with reclaimable mineralized waste management system

This model will make use of forecasted mineral price for future years, to determine whether or not it makes sense to reprocess the stockpiled mineralized rock that was previously below the "cut-off grade". Reprocessing will incur the same costs as before with the inclusion of annual inflation, but the overall cost will be reduced due to no requirements to mine the rock. This scenario will result in an increased ore extraction due to the improved mineral economics compared to current mining practices.

3.2.2. Future technology advances with reclaimable mineralized waste management system

Using current economic data, this scenario will utilize a forecasted increase in processing technology (potential increase in the extraction of minerals from the ore) based on precedents of reprocessing of mine waste at the Mt. Morgan (Carbide Resources Ltd, 2015) mining operation, as well as others. Though this data is much more difficult to forecast than mineral prices, this scenario will utilize historical and current extraction percentages and make an assumption to which the extraction of the mineral could potentially reach. This approach will allow physical depletion and lower grade mineralized rock to be processed due to increased metallurgical recovery; which effectively lowers the "cut-off grade" and increases overall mineral extraction.

3.2.3. Combined future technology advances and increased mineral price with reclaimable mineralized waste management system

This scenario will utilize a forecasted increase in processing technology as well as a forecasted increase in mineral price. This framework will increase overall mineral extraction leading to physical depletion. With the increase in mineral prices and metallurgical recovery, it allows grades which are even lower than the two previous scenarios to be processed with increased revenue. This is the ideal case that accounts for both potential increases in metallurgical recovery and mineral prices which represents the "best case" scenario for future processing of mineralized wastes.

3.3. Forecasted revenue and cost data

From the years 1998 up to the current year (2016) the average inflation rate is relatively constant with only minor fluctuations. The data to be forecasted may use the average inflation rate compounding annually between the years considered of 1.87% (Triami Media, 2016). This value however will not be used in the forecast of the gold price since the historical data is already inflation adjusted based on the actual inflation rates per year, which will make the data very close to the average value but slightly more precise.

3.3.1. Gold price

Gold price has been forecasted based on historical data in order to determine if the reprocessing of mineralized wastes would become viable in the future. This data will be used in the case study of a known gold deposit.

Historical gold data was digitized and plotted in order to determine the basic trend in the price fluctuation in the last 50 years. The initial data was obtained online (Macrotrends, 2016). From the initial plot, a simple linear trend was first determined. If a very basic estimate of future price was to be used, the linear trend would have sufficed. However, it will not adequately represent the nature of the gold industry.

In order to forecast, a single trend was selected to represent the historic data in terms of a sinusoidal function, defining an initial amplitude and frequency. From this initial trend a simple Fourier analysis was completed with the slope being maintained along the linear trend line to try to best fit with the historic data (Fumi et al., 2013).

Fourier analysis utilizes sine waves to represent data sets and converts the trends within the set to sine waves for further analysis. It is typically done in order to analyze data with numerous harmonic frequencies, but the approach and application also applies in simple forecasting.

Figure 8 below is the graph representing the forecasted data alongside the historic data and the linear trend. Because the historic data was provided in USD, it was forecasted in the same unit. This is a simple conversion if other units are required.

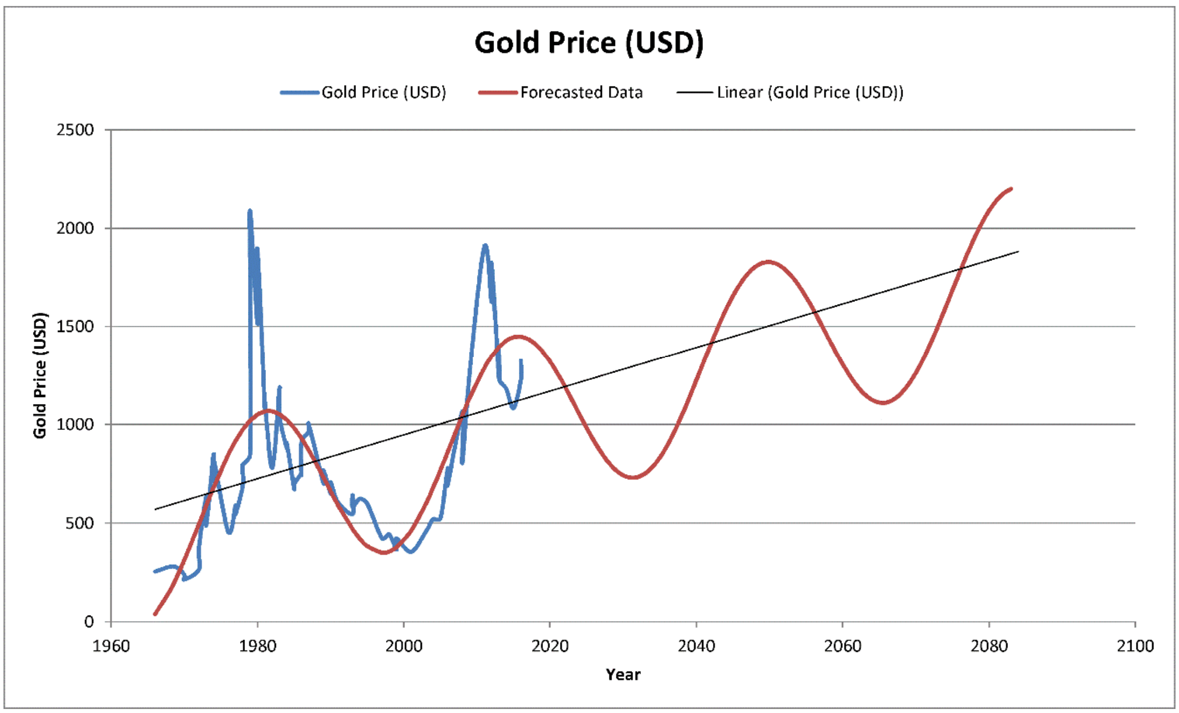

Figure 8 : Forecasted and real gold data

3.3.2. Mining costs – mining, processing, G&A and capital costs

For the purpose of this analysis, a general operating mining cost is to be used to keep a consistent economic forecast which encompasses all mining related costs. The capital and operating costs are both taken from the same source for consistency.

The data used to establish the baseline of the economic costs was taken from Argonaut Gold Pre - Feasibility Study Technical Report on the Magino Project (JDS Energy and Mining, 2016) and Detour Gold Mineral Resource and Reserve Estimate for Detour Lake Property (Detour Gold, 2016) because of the similarity between the sizes of the operations compared to the proposed case study. The estimated costs of these mines are used due to the fact that both mines are open pit gold mines operating or planned to operate in Ontario, Canada. Table 1 shows the values for operating and capital costs of the previously mentioned operation.

Table 1: Capital and operating costs from Argonaut mine and Detour Gold mine with proposed costs (Detour Gold, 2016; JDS Energy and Mining, 2016)

Capital and Operating Costs	Argonaut Costs	Detour Gold Costs	Proposed Costs
Mining Costs ($/Tonne)	8.02	2.76	5.39
Processing Costs ($/Tonne)	6.55	8.14	7.35
G&A Costs ($/Tonne)	0.7	2.47	1.59
Total Cost ($/Tonne)	15.27	13.37	14.32
Inital Capital Costs ($M)	539.8	1110	824.9
Closure Capital Costs ($M)	195.9	115	155.45
Total Capital Costs ($M)	735.7	1225	980.35

3.4. Technology – Gold recovery

The recovery in mining operations is a vital part of determining the sustainability and profitability of the mine. If the ore going into the mill is processed inefficiently then the result is precious commodity ending up in the waste stream.

To maintain consistency with other data that has been taken from industry operations, the processing efficiencies are also taken from Argonaut Gold Pre - Feasibility Study Technical Report on the Magino Project (JDS Energy and Mining, 2016). As seen in Table 2 there is certainly room for improvement in terms of recovery efficiencies, where in theory the recovery efficiencies can reach up to 99%. Table 2 shows the recovery value from the Argonaut operation as well as the value to be used in the proposed frameworks utilizing increased processing efficiencies.

Table 2: Processing efficiencies (JDS Energy and Mining, 2016)

Processing Efficiency	Argonaut	Achievable
Gold Recovery (%)	93.5	99

4. Discussion

This paper has identified a current issue in the conventional methods in the mining industry. The literature review presented has identified the major areas of concerned in the issue of waste management and exhibited not only the issues but why they exits and potential fixes to the problems. The literature also identified other sources confirming the issues being discussed and provided confirmation that the issue of waste management and mining sector sustainability is a growing and concerning danger to the future of humanity.

The conceptual framework that is presented in the paper outlines the variety of scenarios that can be both quantitatively and qualitatively analyzed to further understand the need for proper planning and waste management systems for future reprocessing of mine wastes as a resource.

The first framework that can be analyzed and quantitatively investigated is the conventional mining techniques framework. This framework involves utilizing the cut-off grade to determine which ore is mined and sent to the processing facilities and which rock that is extracted and piled in a waste pile. Though this seems like a reasonable way to perform mining as it is the common practice, it does not address the issue of the waste still containing valuable mineralization in the stream. Another issue that this convention does not address is the fact that mining only occurs until economic depletion rather than to physical depletion. Utilizing this convention leaves behind resources in the ground that have not even been extracted, effectively reducing the overall mineral reserve and global minerals available.

Once the convention mining practices have been investigated, the proposed framework can begin investigation. It is broken into three separate scenarios in which each scenario will be analyzed to emphasize the importance of a proper waste management system. All scenarios in the framework can be analyzed both quantitatively and qualitatively to assess the feasibility and importance of the system.

The first scenario in the proposed framework considers an increase in the mineral price in which one mechanism of the reprocessing feasibility is met. By implementing a waste management system in which the mineral content or grade of the waste is tracked and the waste is properly sorted to allow for the reprocessing to occur in a manner that the most profitable mineralized materials can be processed first. Best practice would be to separate the "highest grade mineralized waste" from the "lowest grade mineralized waste" and subsequently from the material that contains no mineralization. Processing the "highest grade mineralized waste" first and working down to the "lowest grade mineralized waste" is done because the gold industry has a very volatile economic history, causes large fluctuations in the gold price. By ensuring the profitable materials get processed in the time that they are profitable is essential to the effectiveness of the waste management strategy.

The second scenario in the proposed framework considers the technological advances that may occur in the processing and refining technologies while keeping the gold price constant for the sake of this scenario. From Table 2 in this report, the refining efficiency is typically in the range of 93% to 94%, with this scenario considering a practical value of approximately 93.5% (JDS Energy and Mining, 2016). This leaves the maximum potential for the efficiency to increase by 6.5%, though a more practical and achievable increase of up to 5.5%. The other consideration in this scenario is the reduction in processing cost with the increase in processing technology. Though the maximum potential benefit from this scenario in terms of monetary value may not have the same impact as in scenario one of the proposed framework, which has effectively an infinite ceiling, the stability of these benefits are more constant and much more sustainable. This scenario utilizes the same principles as in the previous scenario; with the major difference in this being that any of the profitable ores can be processed once the new technology is in place due to constant gold price, though from a net present value standpoint the highest grade should be done first. Another notable improvement this scenario presents is the potential for a greater percentage of physical depletion of the reserve due to the ability to process and refine more of the mineralization from the materials.

The final scenario in the proposed framework considers both the increase in gold price as well as the technological advances in the processing and refining technologies simultaneously. This scenario seeks to combine what the likely scenarios that will be seen in the future of the industry will hold. Based on the increase in gold price coupled with the increased processing efficiencies, this scenario will provide the greatest benefit in both monetary value as well as physical resource depletion. The scenario uses the same concepts as the previous two, but combining some of the aspects. The processing of the mineralized waste should follow the pattern outlined in the first scenario of the proposed framework, processing the "highest grade mineralized waste" first and working down until the processing is no longer economical. With the combined scenarios the processing will be able to occur earlier in the gold price increase due to the efficiency increase, and will be able to process lower grades than either separately due to the combined positive mechanics.

5. Conclusions and Recommendations

This paper put forth a proposed framework in which the conventional methods in the mining industry are challenged to change in order to provide a sustainable future for the industry, particularly due to the depletion of non-renewable natural resources. By establishing a framework in which waste management is at the forefront of the design of the operation it helps to create a more sustainable operation while promoting the physical depletion of the resources available on earth rather than just the economic depletion of the resources. By utilizing proper waste management systems, it is suggested that the mineralized waste stream can be reprocessed in the future and considered a future resource rather than waste. Though the case study is not completed in this report, this paper presents the methodology in which the investigation will be approached and carried out in order to quantify the impacts of an extensive mine waste management system that allow the waste from the operation to be utilized as a future resource.

In order for the mining industry to continue to meet the rising metal demands, sustainable management of resources is essential. Increase in potential technologies as well as positively trending gold prices will allow for further physical depletion of both new and old mineral reserves. Both the qualitative assessment coupled with the future quantitative investigation will seek to put forth a new framework for the mining and mineral industry to consider in the planning phases to ensure sustainable mining continues into the future. It is also recommended that legislative changes be made for all mineralized waste to be properly stored and documented.

6. References

[1] Carbide Resources Ltd (2015). Mount Morgan PFS Confirms Potential for Low Cost Operation. ASX/Media Announcement

[2] Detour Gold. (2016). Mineral Resource and Reserve Estimate for Detour Lake Property NI 43-101.

[3] Dold, B. (2008). Sustainability in metal mining: From exploration, over processing to mine waste management. *Reviews in Environmental Science and Bio/Technology*, *7* (4), 275-285.

[4] Fumi, A., Pepe, A., Scarabotti, L., and Schiraldi, M. (2013). Fourier Analysis for Demand Forecasting in a Fashion Company. *International Journal of Engineering Business Management*, (Special Issue on Innovation in Fashion Industry),

[5] GEOVIA-Dassault. (2014). GEOVIA GEMS. Ver. 6.5, Vancouver, BC, Canada.

[6] GEOVIA-Dassault. (2015). GEOVIA Whittle. Ver. 4.5, Vancouver, BC, Canada.

[7] Giurco, D., Prior, T., Mudd, G. M., Mason, L., and Behrisch, J. (2010). Peak Minerals in Australia: A Review of Changing Impacts and Benefits.

[8] Gordon, R. B., Bertram, M., and Graedel, T. E. (2006). Metal stocks and sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, *103* (5), 1209-1214.

[9] Hatayama, H., Tahara, K., and Daigo, I. (2014). Worth of metal gleaning in mining and recycling for mineral conservation. *Minerals Engineering*, *76* 58-64.

[10] JDS Energy and Mining (2016). Pre - Feasibility Study Technical Report on the Magino Project NI 43-101. paper Document Number,

[11] Laurence, D. (2011). Establishing a sustainable mining operation: An overview. *Journal of Clean Production*, *19* (2-3), 278-284.

[12] Lottermoser, B. G. (2010). *Mine Wastes: Characterization, Treatment And Environmental Impacts.* Springer, Berlin, Germany,

[13] Lottermoser, B. G. (2011). Recycling, reuse and rehabilitation of mine wastes. *Elements*, *7* (6), 405-410.

[14] Maboeta, M. S. and van Rensburg, L. (2003). Bioconversion of sewage sludge and industrially produced woodchips. *Water, Air & Soil Pollution*, *150* (1), 219-233.

[15] Macrotrends, L. L. C. (2016). Gold Price - 100 Year Historical Chart. Retrieved 2016/04/22/, from: http://www.macrotrends.net/1333/historical-gold-prices-100-year-chart

[16] Meadows, D., Randers, J., and Meadows, D. (2005). *Limits to Growth: The 30 Year Update.* Earthscan, London, UK,

[17] Mining Minerals and Sustainable Development (2002). *Breaking new ground: Mining, Minerals and Sustainable Development project.* Earthscan, London, UK,

[18] Ontario Ministry of Northern Development of Mines (2016). The Mining Act. Retrieved 2016/09/06/, from: http://www.mndm.gov.on.ca/en/mines-and-minerals/mining-act

[19] Prior, T., Giurco, D., Mudd, G. M., Mason, L., and Behrisch, J. (2012). Resource depletion, peak minerals and the implications for sustainable resource management. *Global Environmental Change*, *22* (3), 577-587.

[20] Tilton, J. E. (1996). Exhaustible resources and sustainable development: Two Different Paradigms. *Resources Policy*, *22* (1-2), 91-97.

[21] Tilton, J. E. and Lagos, G. (2007). Assessing the long-run availability of copper. *Resources Policy*, *32* (1-2), 19-23.

[22] Triami Media, B. V. (2016). CPI Canadian Inflation. Retrieved 2016/09/06/, from: http://www.inflation.eu/inflation-rates/canada/historic-inflation/cpi-inflation-canada.aspx

[23] Weber, I. (2005). Actualizing Sustainable Mining: Whole Mine, Whole Community, Whole Planet through Industrial Ecology and Community-Based Strategies. Weber Sustainability Consulting

[24] Willett, K. (2002). Managing Australian Mineral Wealth for Sustainable Economic Development. International Institute for Environment and Development

[25] Williamson, H. F. (1945). Prophecies of Scarcity or Exhaustion of Natural Resources in the United States. *The American Economic Review*, *35* (2), 97-109.

Open Pit Mine Planning and Waste Management Optimization: A Review of Models

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Abstract

Open pit mine planning involves extracting the mining blocks in specific and strategic sequence from the mine in order to obtain the highest net present value. Open pit planning takes into consideration variety of constraints such as production, grade blending and pit slope limitations. Long-term production planning (LTPP) and scheduling are key factors in deciding whether mining projects should continue or be suspended. Since the 1960s literature has supported the application of mathematical programming algorithms for optimization of LTPP and scheduling in open pit mine operations. In this paper, heuristic, meta-heuristic and deterministic optimization approaches, as well as application of artificial intelligence and uncertainty-based approaches to mine planning and waste management have been reviewed and discussed. Limitations of current mine planning models have been outlined.

1. Introduction

The five main steps in the process of recovering valuable material from the earth's crust are: prospecting, exploration, development, exploitation and reclamation. Visual and physiochemical evaluations are used by geologists to discover the valuable mineral deposits. Then drillholes are drilled and samples taken to determine the mineral concentration and the variability of the deposit. Based on the economic parameters, and after representative tonnage-grade curves, the prospective profits from extracting the ore are determined using different interpolation and simulation techniques. The overburden is removed, geometrical preparations of infrastructure and production capacity is calculated, and detailed engineering design is implemented in the development stage. Ore is recovered using open pit or underground techniques in the exploitation stage. Processing plant, stockpiles and waste dumps are the destinations of the extracted ore and waste. Finally, the mining site is reclaimed as close as possible to its original state (Hochbaum and Chen, 2000; Newman et al., 2010).

In order to guarantee mining industry's goal which is maximization of profits, each of the mining steps should be planned and carried out carefully to find the feasible plan for ore extraction. To maximize the overall profitability of the mining project and to minimize deviation from target production, optimization models are being introduced in the mine planning process primarily for development and exploitation stages.

This paper will review mathematical programming models such as linear programming, integer programming, mixed integer linear programming, dynamic programming and goal programming. It will focus mainly on long term mine planning and waste management of oil sands resources. It will be organized as follows: open pit mining, open pit mine planning and scheduling, waste management, integrating open pit mine planning and waste management, oil sands mining and different approaches of modeling the optimization problem. Finally, the limitations of current mine planning and waste management models will be discussed.

2. Open Pit Mining

Mines could be shallow, deep and long depending on the natural occurrence of the deposit. Open pit or surface mining is defined as the method of recovering valuable minerals from deposits fairly near the earth's surface. Open pit mining is the most common, productive and oldest method of mining ore from the ground (Newman et al., 2010). The mining rate includes both mining the ore and removing the waste. The production rate in open pit mines could be 20,000 to 100,000 tonnes per day (Scott Dunbar, 2012). There are several factors which determine whether ore will be extracted through surface or underground mining operations. These are: 1) amount of the overburden, 2) limited area for dumping the waste, 3) unstable pit walls and 4) environmental considerations (Newman et al., 2010). The overburden (the material that covers the deposit and contains no economic quantity of minerals) in addition to waste rock within the deposit (interburden that currently contains no economic quantity of minerals) must be removed to gain access to the mineralized zone. The mineral content that distinguishes ore from waste (cut-off grade) can change depending on the market conditions and the availability of extraction technology. It is possible that material which has been considered waste becomes a potential reserve (Scott Dunbar, 2012).

The surface of the land is continuously excavated by mining processes until the end of the mine life resulting in a deep pit. Benches are used for extracting the ore (Hochbaum and Chen, 2000; Ben-Awuah and Askari-Nasab, 2011). The ore is taken to the processing plant and the result of a mineral separation process in the concentrator (known as tailings) is taken to tailings containments or ponds Fig. 1 Economic and technical factors, in addition to production constraints determine the size and shape of the pit. There are a series of intermediate pits sometimes referred to as pushbacks before the ultimate pit that exists at the end of the mining process (Lerchs and Grossmann, 1965; Askari-Nasab, 2006).

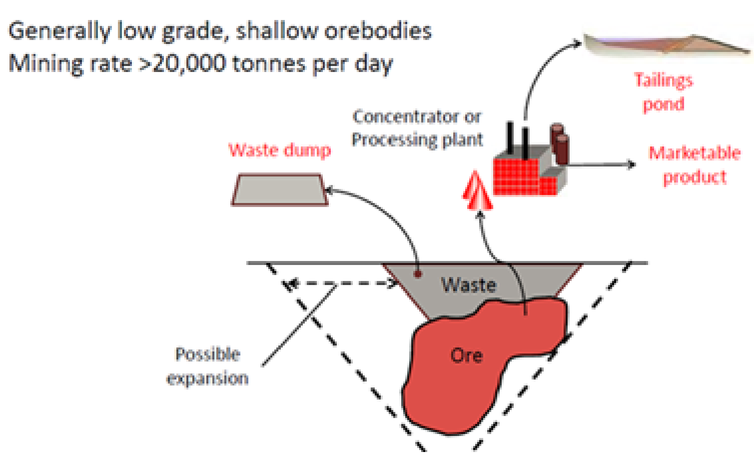

Fig. 1. Open pit mining operations (Scott Dunbar, 2012)

3. Open Pit Mine Planning and Scheduling

Extracting the blocks from the mine in specific sequence to give the highest net present value (NPV) is known as open pit mine planning and scheduling. This is subject to a variety of production, grade blending and pit slope constraints (Whittle, 1989). Minimizing the mining costs and maximizing the production considering the quality and the operational requirements are the goals of mine production planning (Newman et al., 2010).

According to Jardine and Evans (1989), mine production planning and scheduling includes six repeated tasks during life of mine: 1) extracting point data such as drillhole data and then 3-D geological modeling of deposit, 2) designing the mine pit limits, 3) building mining blocks and assigning reserve features to each block, 4) determining the extraction rate and sequence of blocks, 5) simulating the block extraction, and finally, 6) reporting the results of extraction sequence.

In mining projects, Chicoisne et al. (2012) describe the mine planning phase as: 1) Block model determination: this step consists of drilling in different locations and depths of the mine. Obtaining samples of material for grade and densities interpolation, dividing the orebody into blocks of equal size and an estimated tonnage and mineral grades are assigned to each block. As a result, compute the estimated extraction profit for each block in the model. The economic block model then is a block model with profit attributes. 2) Ultimate pit limit is defined as the area in which extraction will take place. Before any block can be extracted, all blocks immediately above and at certain angles must also be removed Fig. 2. To determine the ultimate pit limit, it is necessary to determine slope angle. This depends on the structural composition of the rocks and the location and depth of each block. 3) Production scheduling involving the decision of which blocks and when and how they should be extracted. First, determine a set of pushbacks. Pushbacks are subdivided into groups of blocks at the same vertical level (or bench) known as bench-phases. Finally, bench-phases are scheduled a time of extraction (Chicoisne et al., 2012). Deviations from optimal mine plans may result in significant financial losses, future financial liabilities, delayed reclamation, and resource sterilization (Ben-Awuah and Askari-Nasab, 2011).

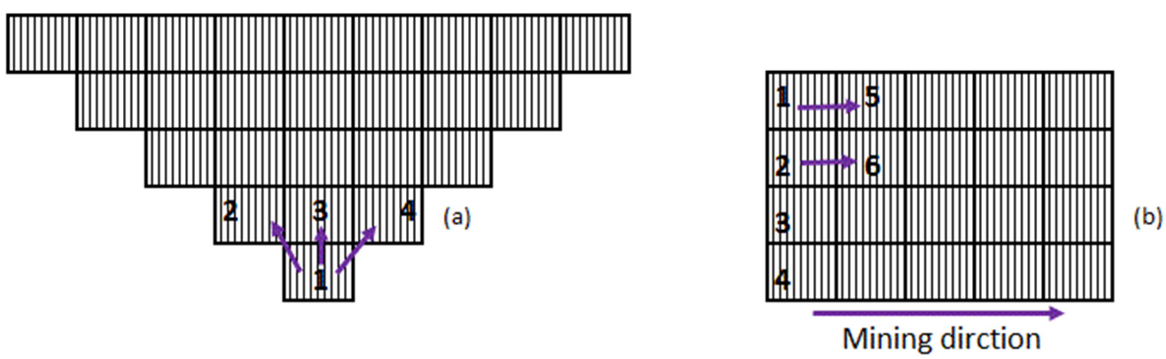

Fig. 2. Block extraction precedence: (a) cross sectional view and (b) plan view modified after Ben-Awuah and Askari-Nasab (2011)

The final pit limit defines the size and shape of the open pit mine at the end of the mine life subject to economic, technical and operational constraints. Cut-off grade or the grade that distinguishes ore from waste is required. It depends on the current and future states of the mine simultaneously. The pit limits are used in determining the boundary layouts and location of mine infrastructure such as processing plants, tailings facilities, waste dumps and mine offices. The location and type of haulage ramps and other infrastructure are other required aspects of designing the open-pit mine, in addition to long-term decisions regarding the size and location of production and processing facilities.

There are many techniques used to find the ultimate pit limits such as the heuristic floating cone technique (Osanloo et al., 2008), the 2D algorithm based on dynamic programming, the 3D algorithm which uses graph theory that is widely accepted in the mining industry (Lerchs and Grossmann, 1965). These are in addition to maximum network flow algorithm (Johnson, 1969) and transportation algorithms (Osanloo et al., 2008). Without the final or ultimate pit limit, the open pit mining of a given deposit will be uneconomic. The optimum final pit limits therefore define the pit outline containing the material extracted to give the total maximum profit whilst satisfying all operational constraints (Caccetta and Giannini, 1990; Ben-Awuah, 2013).

Long-term production planning focuses mainly on ore reserves, stripping ratio (the quantity of waste to be removed in order to obtain one unit of ore), and major annual investment plans (Newman et al., 2010). Three time ranges are included in production planning; i) short-term, between a month and a year, ii) medium-term, between one to five years and iii) long-term, up to 30 years which is the focus for this paper.

4. Waste Management

For the mining industry, managing waste is challenging. Mining operations result in significant amounts of waste material with different types, such as overburden, waste rock (low grade ore), tailings, slags (non-metallic by-products from metal smelting), mine water, water treatment sludge, and gaseous wastes (Scott Dunbar, 2012). Efforts have been made by mining companies to reduce the environmental impact of mining activities and minimize their footprint. Thanks to technological developments and changes in management methods many of the adverse effects of mining affecting its surrounding environment are now avoidable.

Waste management plans are usually developed before the mine is constructed. There is integration between reclamation of waste rock dumps and tailings ponds, and the designs of new mines. The main concern of mining environmental management is the adverse effect of waste materials and tailings disposal on the surface, i.e. tailings containments and waste dumps. Depending on the composition of ore type being mined and the processing techniques used at the mine site the mine waste is different in type, amount and properties. In other words, every mine produces different waste that requires its own classification, estimation, monitoring and treatment. Some of these materials may be acid generating which must be properly managed to protect the environment (Rashidinejad et al., 2008).

In the LTPP, preventing pollution is easier and less expensive than after pollution has been created. Pollution problems result in high capital and operating costs and long-term liabilities. In other words, waste management practices should focus on "prevention" rather than "treatment". Researchers have concentrated on promising prevention techniques such as layering and blending through strategic mine planning. The best way to eliminate these liabilities is minimization of the waste and pollution at the source in the first place (Cheremisinoff, 2003). Large quantities of acid generating waste material and tailings have been inherited from past mining operations. Mine design processes still focuses mainly on technical mining, financial considerations and potential impacts of waste disposal on the environment (Rashidinejad et al., 2008). There are two major categories of environmental impacts from mine sites waste disposal: the loss of productive land after being used as waste storage area, and contamination of adjacent surface and groundwater (Scott Dunbar, 2012). Continuous research in minimizing waste and finding alternative uses for mineralized mine waste is essential for effective waste management.

5. Integrating Open Pit Mine Planning and Waste Management

An important discussion on surface mining operations is mine planning and waste disposal management. Mine closure or future financial liabilities can result from poorly planned mining operations. Modelling an integrated mine planning system adds more difficulty to the LTPP problem (for instance, incorporation of waste disposal planning). According to McFadyen (2008), oil sands waste management is predominately a post-production scheduling optimization activity. Scheduling of dyke material is carried out after mining has started and this may result in inconsistent production of dyke materials at different periods during the mine life. Ben-Awuah (2013) developed an incorporated mine planning and waste management strategy for in-pit and external tailings facilities for oil sands mining operations. His approach requires a new and more systematic method for planning of oil sands mining operations.

Available literature on oil sands mining lacks the framework for planning of oil sands resources which has a unique scenario for waste management. The material required for construction of dykes come mainly from mining and processing operations; as overburden, interburden, and tailings coarse sand (Fauquier et al., 2009; Ben-Awuah, 2013). Upstream construction, downstream construction, and centerline construction are the main methods for dyke construction. In addition, with respect to the regulatory requirements from Directive 074, waste disposal planning must be considered in a close relation to the oil sands mine planning system (McFadyen, 2008).

Challenges which arise during the integration of oil sands waste disposal and production scheduling optimization include: 1) Intractable size of the optimization problem resulting from scheduling different material types with multiple elements for multiple destinations; 2) The need to integrate the availability of in-pit disposal areas with dyke construction planning on a continual basis throughout the mine life to support the tailings storage plan; 3) The limited lease areas for oil sands operators require the maximum use of in-pit and ex-pit tailings facilities for sustainable mining; 4) NPV derived from production scheduling and sustainable mining derived from waste disposal planning are the two targets that cause difficulty in deciding which must be traded off and at what cost (Fauquier et al., 2009).

Although a team of engineers work on dyke construction planning, there is no guarantee that the developed plan meets all the material requirements for dyke construction in all periods and the resulting NPV is maximized (Fauquier et al., 2009). Ben-Awuah et al. (2012) and Ben-Awuah (2013) have introduced a pioneering effort in developing an integrated mathematical programming model for incorporating oil sands mine planning and waste management using mixed integer linear goal programming (MILGP) in an optimization framework.

Ben-Awuah et al. (2012) have implemented a mathematical model for an integrated oil sands production scheduling and waste disposal planning system. This takes into consideration multiple material types, multiple elements and destinations, directional mining, waste management and sustainable practical mining strategies. Ben-Awuah (2013) reports that the MILGP model is a powerful tool for optimizing LTPP in oil sands mining. The model provides a robust platform for integrating waste disposal planning. It is an efficient production scheduling optimization approach that uses penalty and priority parameters, and goal deviational variables. However, the model implementation results in a large-scale optimization problem, and according to Badiozamani (2014) it does not include tailings slurry, the most important waste in oil sands mining.

Oil sands mines require large tailings containments that will affect the landscape. Reducing the size and need for tailings containments, and increasing the speed with which they can be reclaimed, are challenges for oil sands mining companies. Since the capacity for tailings storage is limited to the lease area, mining cannot be scheduled without considering potential tailings production. An integrated model for LTPP with the concept of tailing management is proposed by Badiozamani (2014). He integrates reclamation material handling and tailings capacity constraints to provide capacity for in-pit tailings facility.

In order to maximize NPV, Badiozamani (2014) determines the destination for each extracted parcel. The selective mining units are followed using mining aggregates. He generates maximum NPV, minimizes the material handling cost of reclamation, and the tailings volume produced downstream meets the tailings capacity constraints in each period. The author integrates mine planning with tailings management in terms of composite tailings (CT) production and deposition, in the mine planning optimization framework. Mine planning, tailings management, waste disposal scheduling and reclamation planning are four areas that should be integrated in order to achieve a more robust schedule (Badiozamani, 2014).

6. Oil Sands Mining

In North America, oil sands mining is one of the most evolving industries. Oil sands mining started in the 1960s with surface mining operations that uses Clark hot water extraction (CHWE) to extract bitumen from the bearing formation. Truck-shovel system is used to extract northern Alberta oil sands reserves which are mostly located near the surface (Clark and Pasternack, 1932; Clark, 1939). Muskeg (the overburden), Pleistocene unit and Clearwater formation (both are waste rocks); McMurray formation (carries the bitumen, the element of interest) and Devonian carbonates (marks the end of the oil sands deposit) are the five main rock types in oil sands formation Fig. 3 (Ben-Awuah, 2013; Badiozamani, 2014).

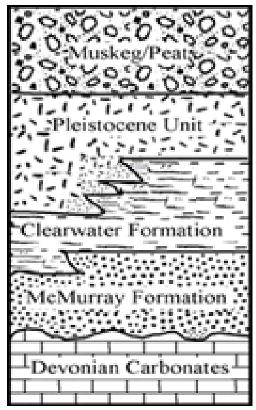

Fig. 3: Vertical soil profile sketch of an oil sands formation (Ben-Awuah, 2013)

In oil sands mining, huge amounts of bituminous sands are sent to the processing plant and these results in a mixture of water, fine materials, sands and residual bitumen - known as tailings which represent more than 80% of the processed ore. The waste material (overburden and interburden) are sent to waste dumps or used for dyke construction. In-pit and ex-pit tailings dykes used for storing tailings are constructed using overburden and interburden seams in addition to tailings coarse sands (TCS) resulting from the processing plant Fig. 4 Accordingly, waste management is a significant part of oil sands mining operations that may lead to economic liabilities if not well managed (Ben-Awuah, 2013; Badiozamani, 2014).

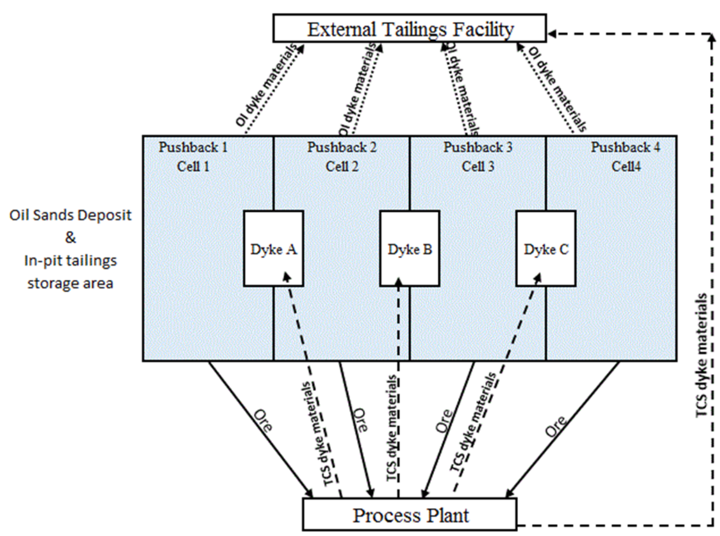

Fig. 4. Conceptual mining model: mining and waste management strategy modified after Ben-Awuah (2013)

In oil sands mining, waste and tailings management requires special geotechnical considerations and tailings management techniques (Boratynec, 2003; Ben-Awuah, 2013). Deviations from optimal mine plans will result in significant financial losses, future financial liabilities, and delayed reclamation. There are three significant aspects in dealing with oil sands tailings (the most unwanted by-product of oil sands processing). First, the greenhouse gas emissions resulting from CHWE process. Second, the environmental challenges due to the toxicity of the tailings resulting in contamination of fresh water table by the polluted tailings water leaks. In order to dewater tailings and prepare the tailings containment area for reclamation, composite tailings (CT) production technologies are used. The dewatering technology is based on adding gypsum as a coagulant to aid production of mature fine tailings (MFT) and to increase the dewatering rate of the MFT (Rodriguez, 2007; Singh, 2008). Third, space limitation increases the need for in-pit tailings containment (storage space) since more mining processes lead to a further volume of tailings slurry.

Presently, plans for tailings and reclamation are prepared after the optimization of long-term mine production plans. The optimization of LTPP problems is used as an input to the tailings and reclamation plans (Badiozamani, 2014). The requirements of Directive 074 issued by the Alberta Energy Regulator (AER) mandate oil sands operators to publish their waste disposal and tailings plans (McFadyen, 2008; Ben-Awuah and Askari-Nasab, 2011). Overburden, low-grade interburden (OI), and tailings coarse sand (TCS) (generated from processing of bituminous sands) are used for dyke construction for tailings storage and as a reclamation material at the reclamation stage. This makes it very important to incorporate waste management, tailings planning, and reclamation planning in the long-term mine planning optimization framework. It is important that the sequence of extracting the ore and the supply of material used for dyke construction be continuous to guarantee uniform supply to the plant and for dyke construction throughout the mine life (Fauquier et al., 2009). An integrated oil sands mining operation including material flows(Fig. 5), solid waste and tailings management is provided in detailed description by Ben-Awuah et al. (2012) although in general there is limited research work in this area (Ben-Awuah and Askari-Nasab, 2011; Badiozamani, 2014).

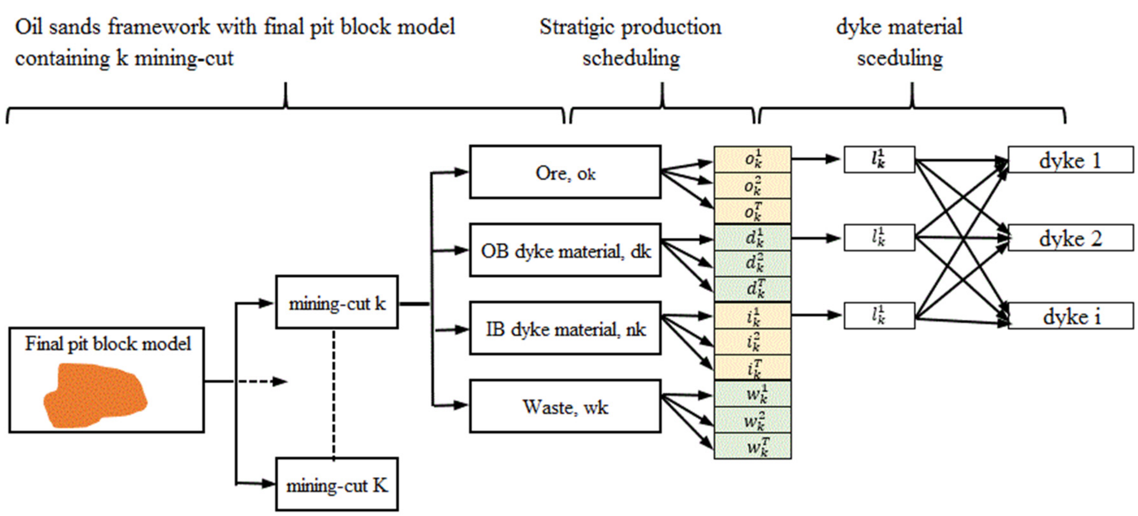

Fig. 5. Schematic representation of oil sands mining and solid waste material flow modified after Ben-Awuah (2013)

7. Mine Production Planning Models and Algorithms

Solving LTPP problems should satisfy the objectives of medium and short-term scheduling otherwise the optimality of the solution might be affected. First, the main input, the geologic block model for open pit mine design and scheduling processes, should be prepared. It is a quantitative definition of the available resource. The deposit is divided into fixed size blocks. The exploration drilling pattern, ore body geology and mine equipment size are the main points that have to be considered in the selection of block dimensions. Next, using available estimation techniques such as inverse distance weighted interpolation technique, weighted moving averages and Kriging geological characteristics of each block (grade) are assigned. Using financial and metallurgical data, the economic value of each block is also calculated. It should be noted that this value excludes the cost of accessing the block. The economic present value of the block can then be obtained by discounting the original value to time zero, using a discounted rate (Osanloo et al., 2008). Based on a deterministic metal price, each block is assigned a value equal to the gross value of its metal content minus the applicable production, processing and refining costs (Abdel Sabour and Dimitrakopoulos, 2011).

In the literature, the LTPP and scheduling methods can be divided into main categories: 1) heuristic algorithms, 2) deterministic algorithms, 3) application of artificial intelligence techniques, and 4) uncertainty based approaches. Deterministic approach assumes the input values and parameters are known and fixed, while uncertainty based approaches considers some input parameters as uncertain.

7.1. Heuristic and Meta- Heuristic Optimization Approach

Some popular mine production scheduling software are developed based on heuristic methods such as XPAC AutoScheduler software (Runge Limited, 2009), Whittle (Gemcom Software International, 2012) and NPV Scheduler (Datamine Corporate Limited, 2008). XPAC AutoScheduler software is developed based on Gershon's proposed heuristic algorithm that generates cones upward from each reference block and determines the possibility of the block to be part of the schedule. According to the importance of mining a block at a certain time, a list of exposed blocks and a ranking of those is updated through the algorithm based on a factor called the positional weight. This weighted function is used to determine the removal sequence. The final pit determination depends on the number of reference blocks that will be used in addition to the sequence of selecting those blocks. The solution is fast and accurate, however, the ultimate pit is not necessarily optimal (Gershon, 1987; Laurich, 1990; Runge Limited, 2009).

Another popular heuristic is introduced by Lerchs and Grossmann (LG) (1965). It has been used in strategic mine planning software, such as Whittle and NPV Scheduler based on the concept of parametric analysis (Osanloo et al., 2008). The LG algorithm provides an optimal solution to the ultimate pit limit. There are many number of strategies with different discounted cash-flows of reaching the ultimate pit. The strategy that would maximize the discounted cash-flow while meeting all the physical and economic constraints is the optimal production schedule. The parametric analysis generates a series of nested pits based on varying the price of the product and finding an optimal pit limit using LG algorithm for that price. The nested pits are grouped into pushbacks, each one associated with similar resource usage. Pushbacks then are used as a guideline to identify clusters of high grade ore and to determine the production schedule. The algorithms are fast to solve and the result is accurate. The main disadvantage of heuristic algorithms is that there is no measure of quality, moreover, the solution will not guarantee optimality which in mega mining projects may cause financial losses (Askari-Nasab and Awuah-offei, 2009; Newman et al., 2010).

On the other hand, solving LTPP problems using meta-heuristic approaches such as genetic algorithms, simulated annealing, etc. have depicted to be effective for large-scale NP-hard problems, especially in the wider field of production planning and scheduling. Denby and Schofield (1994) presented a meta-heuristic model based on genetic algorithm. Their model is able to optimize production planning and ultimate pit limit at the same time. In addition, they achieved an acceptable result in a good time. However, the result changes as they re-run the model and the model do not take into account the effect of pit volume on the unit cost.

7.2. Deterministic Approaches for LTPP

Long term production scheduling problems are very complex to solve. Since the 1960s, many researchers have studied and applied Operations Research (OR) methods in mine production scheduling. Several types of mathematical formulations have been considered for the LTPP problems and have been studied widely in the literature. A variety of deterministic optimization methods including Linear Programming (LP), Integer Programming (IP) and Mixed Integer Linear Programming (MILP) are commonly used, in addition to Dynamic Programming (DP) (Osanloo et al., 2008) and Goal Programming (GP) that have the capability of considering multiple material types, elements, and destinations.

7.2.1. Linear Programming and Mixed Integer Linear Programming Approach for LTPP

Johnson (1969) introduces linear programming as a mathematical programming model to the mine planning research area. He proposes a linear programming model for the long-term, multi-destination and open pit production planning problem along with a decomposition approach to solve the problem. That means a large multi-period model is divided into sub-models considering one period at a time. For each period the sub-model generates optimum results. The author's model considers discounted values of revenues and costs, different processing types and dynamic cut-off grade. After solving all sub-problems, the original problem is relatively simplified. This initial model uses continuous variables to control precedence constraints which would result in fractional extraction of blocks and infeasible solutions. The results are not optimum for the whole multi-period model. Moreover, due to the size of the problem it is computationally intractable. The precedence of block extraction is not satisfied and that results in some percentage of the overlaying blocks being suspended in air (Gershon, 1983).

The initial LP model was subsequently modified by Gershon (1983) to MILP. He considers a set of binary variables to satisfy the precedence of block extraction. He assigned four different decision variables for each block. For a typical open pit long-term scheduling problems, the number of blocks may reach millions, and the number of scheduling periods could be about forty years for a life-of-mine production schedule. The model can handle multiple ore processing options and multiple grades. However, the numbers of binary variables make the model intractable for real size mine planning projects. Although MILP has significant potential for optimizing production planning in open pit mines with the objective of maximizing the discounted cash flow, when it comes to large-scale projects it generates too many binary variables that make it intractable to solve with the current state of hardware and software.

7.2.2. Dynamic Programming Approach for LTPP

A dynamic programming (DP) model that maximizes the NPV, subject to production and processing constraints is presented (Osanloo et al., 2008). This method considers both the time value of money and block sequencing to determine the ultimate pit limit. However, it cannot be applied to large scale problems, and there is no guarantee that mining and milling constraints will be satisfied. Based on a combination of heuristics and DP, Newman et. al.(Newman et al., 2010)(Newman et al., 2010)(Newman et al., 2010)(Newman et al., 2010)(Newman et al., 2010) propose their methodology (Newman et al., 2010). They claim that the ultimate pit limits, the cut-off grade, the mining sequences and production scheduling are related to each other and without the knowledge of one variable the next variable cannot be determined. Their method brings the required simultaneous solution to the problem. Currently, there are some researchers that argue that DP is intractable for large problems and Lagrangian approach is theoretically optimal and suitable for large problems.

7.2.3. Goal Programming Approach for LTPP

Liang and Lawrence (2007) state that goal programming allows for flexible formulation and the specification of priorities among goals. GP is also used by Chanda and Dagdelen (1995). Their model tries to minimize the deviation from goals after setting up the blending problem with multiple goals. The model was tested for a coal mine deposit, but due to some interactions involved in solving the problem, optimal solution cannot always be guaranteed. A mineral dressing criteria was defined by Esfandiri et al. (2004) and used in the optimization of an iron ore mine. A binary non-linear goal programming model was defined based on multiple criteria decision making and the deviations for economics, mining and mineral dressing functions were minimized. This formulation was solved using LINGO software. The model was found to have limitations and constraints that are numerous for practical application.

Ben-Awuah (2013) has formulated the oil sands long-term mine production scheduling and waste disposal planning problem using a combination of mixed integer and goal programming formulations. He claims that using GP is appropriate for his framework because, based on the importance of the goals; the structure will allow the optimizer to achieve some goals while others are traded off. The important goals will be selected according to the impact of a deviation from their targets on the mining operations. The goals to be achieved are the mining and processing targets, and OB, IB and TCS dyke materials targets in tonnes for all mining locations, and processing and dyke construction destinations. The constraints are: grade blending, variables control and mining-panels extraction precedence constraints. This technique is a good choice when there are many goals and some of them need to be chosen among others. It is a flexible technique and allows for some level of interaction between the decision maker and the optimization process (Zeleny, 1980; Hannan, 1985). According to Ben-Awuah (2013), solutions within known optimality limits are expected using exact solution methods for LTPP problems. For the resulting production schedule, a higher NPV is guaranteed as the solution gets closer to optimality.

7.3. Clustering Technique

To reduce the number of variables some authors try to classify the large amount of data into relatively few classes of similar objects. This classification is known as aggregation or clustering. Newman et al. (2010) proves that nonlinear programming (NP) model is NP-hard. Instead of solving this NP-hard problem, there are some non-deterministic algorithms that have been developed by many authors. Hard and fuzzy clustering are two main clustering algorithms. The first one determines whether each unit belongs to a group or not and the second decides whether each unit belongs to each group to a certain degree. Both clustering algorithms can be organized to hierarchical clustering, partitional clustering or overlapping clustering. Since all blocks must belong to only one cluster, hierarchical and partitional clustering can be used in mine planning. Feng et al. (2010) state that although hierarchical clustering methods generate better results they are computationally expensive.

Boland, et al. (2009) propose a solution procedure based on an aggregate level for the order of extraction decisions while block level is used for processing decisions. They are able to report notable progress in CPU time for their model, however, the degrees of freedom of the optimization problem is reduced by using the aggregated blocks. Askari-Nasab et al. (2010) and Askari-Nasab et al. (2011) have used some block clustering techniques for MILP to reduce the size of the LTPP problem prior to optimization (Fig. 6). They clustered mining-blocks according to their properties such as spatial location, grade and rock type to form larger units known as mining-cuts (Boland et al., 2009; Ben-Awuah, 2013; Tabesh, 2015).

As Barbakh et al. (2009) state, there are many data clustering techniques through heuristic or meta-heuristic algorithm such as hierarchical clustering (Johnson, 1967), k-means clustering (MacQueen, 1967), and fuzzy c-means clustering (Dunn, 1973). In addition, there are some other techniques used to reduce the size of the problem. For example, defining fundamental trees (Ramazan et al., 2005; Ramazan, 2007) and mining-panels that are introduced by Ben-Awuah (2013). In order to decrease the number of binary variables in the IP model, Ramazan et al. (2005) aggregate ore and waste blocks together. Mining panels are generated from the intersections of pushbacks and mining benches, and within the boundaries of mining panels mining-cuts are defined and can be used for destination decisions. Clustering and paneling are powerful techniques that are used to provide larger units that follow the practical selective mining units and reduce the number of decision variables which results in increasing the speed of the algorithm. Clustering reduces the gap factor and it is more accurate because most open pit mines are extracted in mining-cuts not in blocks (Tabesh, 2015).

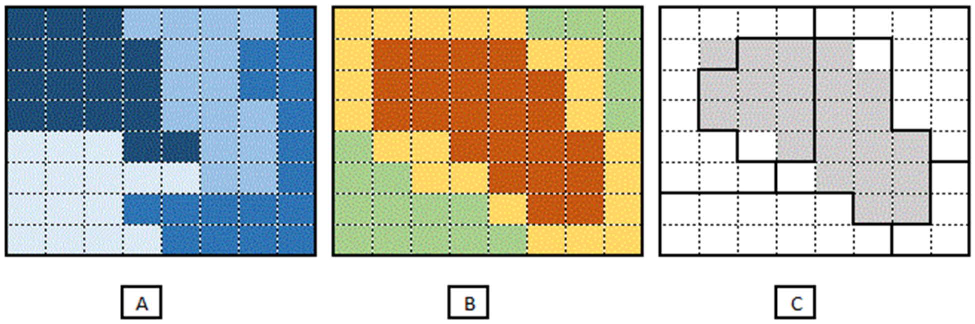

Fig. 6. Schematic view of clustering: A) shows rock types, B) shows grade distribution, C) shows the resulting mining-cuts modified after Badiozamani (2014)

Reducing the number of decision variables before solving the problem is another way of reducing the size of the problem. The idea is that the accumulated mining (and processing) capacities are known and limited for each period in advance, and the total tonnage above any specific mining-block is known based on the precedence order of extraction. Accordingly, it can be decided whether a specific mining-block is accessible in certain periods or not so many variables may be eliminated from the model (Bley et al., 2010; Martinez and Newman, 2011; Tabesh, 2015).

To sum up, although the above mentioned methods significantly decrease the number of binary variables required and enhance the application of MIP in large mineral deposits, in-situ orebody variability is not considered and all inputs are considered without uncertainty. Clustering of mining-blocks are a reasonable assumption for long-term mine planning problems and make the problem tractable, however, they will reduce the accuracy of the solution which might result in losing the optimality of the original problem.

7.4. Application of Artificial Intelligence Techniques and Genetic Algorithm

A method that is a combination of dynamic programming, stochastic optimization and artificial intelligence with heuristic rules to solve LTPP problems is proposed by Underwood and Tolwinski (1998). The method is practical for mining operations since it considers all production constraints. It finds the ultimate pit limit and obtains the production schedule at the same time. However, optimal solution cannot be proven mathematically and a feasible solution for large problems is not guaranteed.

Another method based on genetic algorithm and simulated annealing for production scheduling and ultimate pit limit was proposed by Osanlooet al. (2008). It generates a random pit population and evaluation of a suitability function to obtain the production schedule and ultimate pit limit simultaneously. Although it is flexible, there is no measure of optimality for the solution. To reduce the size of the optimization problem, aggregated blocks and a genetic algorithm are used and compared. Although the practical consequences of aggregation is not mentioned, it has been found that CPLEX reaches the solution in about two to four times longer than the genetic algorithm does.

Osanloo et al. (2008) developed a simulative optimization model to determine the ultimate pit limit using dynamic programming technique. It determines the block extraction sequence and the real unit costs for each new pit condition. After some iterations and according to the nature of the dynamic programming technique, the size of the problem becomes huge. The model solves the ultimate pit limit and production scheduling problems simultaneously. It is unique because of its ability to estimate unit cost for each new pit scenario. The model considers all types of operating constraints, such as transportation, stockpiling, grade blending and plant facilities. However, it is not efficient for medium and large deposits. Also, even for small problems the optimal solution is not guaranteed.

Another method that also generate the ultimate pit limit and production schedule at the same time is the intelligent agent-based mine planning simulator IOPS. Askari-Nasab (2006) developed an intelligent agent-based simulator for surface mine planning that has a component which simulates pushbacks and the intelligent agent learns the optimal pushback using reinforcement learning method. There is no guarantee that the results will reach the theoretical optimum solution. These techniques are based on frameworks that theoretically will reach near optimal solutions, given sufficient number of simulation iterations. The disadvantage of these methods is that there is no quality measure for solutions provided compared against the theoretical optimum.

7.5. Uncertainty Based Approach

Since deterministic solution methods are incapable of dealing with stochastic variables when solving large scale LTPP problems, many researchers have tried to solve LTPP problems using the uncertainty based approach. Results have shown that some (or significant) differences between actual production and theoretical expectation might exist due to grade and geological uncertainties (the two important sources of risk in mining industries), especially in early years of production. As hardware, software, and solution techniques develop, more accurate models are expected (Osanloo et al., 2008; Newman et al., 2010; Gholamnejad and E., 2012). In literature, there are few works on uncertainty based methods.

The geologic block model is the main input data for optimizing LTPP problems. There are some random input variables such as grades, costs, prices, and recoveries. In deterministic approaches, the best estimated values of these random variables available at the optimization time are used. The optimal solution can be affected by uncertainties related to the input parameters. A rerun is required when new data becomes available. This updating is aligned with the mining industry practices. Uncertainty can be reduced only by getting more data over time. Most research has focused on minimizing the negative impact of grade, geological, and market uncertainties on production schedules.

Dimitrakopoulos and Ramazan (2008) first incorporated geological uncertainty into open pit mine planning. Some researchers have shown the consequences of grade uncertainty and the economic value of each block in production schedules. In the early years, a survey for mining operations show that 60% of mines had 70% less production than designed capacity (Osanloo et al., 2008). The key uncertainty factors are geological and mining, financial and environmental. Geological uncertainty is a major contributor in failing to meet production targets and the financial expectations of a project.

A framework for incorporating risk in open pit mine planning was proposed by Osanlooet al. (2008). He used stochastic orebody models and sequentially generated a production schedule. However, sequential procedures are shown to be inefficient and cannot produce a global optimal schedule considering uncertainty. Osanloo et al. (2008) classifies uncertainties involved in mine planning as: i) orebody model and in-situ grade uncertainty, and material type distribution; ii) extraction capacities and slope consideration, and iii) capital and operating costs uncertainties. Dimitrakopoulos and Ramazan (2008) present a stochastic linear integer programming (SIP) model to generate the optimal production schedule using equally probable stochastically simulated orebody models as inputs. They put a penalty function for the cost of deviation from the target production and use linear programming to maximize NPV minus the penalty costs. They are able to generate an optimum solution that can increase NPV by adding some constraints. However, the difficulty and CPU time required to solve the optimization problem increased. Moreover, the model is not dynamic and flexible to new information that is developed during the mine life.

Some notable research is presented in the area of stochastic pushback design. Osanloo et al. (2008) presents a multi-stage heuristic framework to generate a final schedule which considers geological uncertainty. A basic input to this framework is a set of realizations (equally probable scenarios of the orebody). The author reports significant improvement on NPV in the presence of uncertainty however, there are some disadvantages for the model: (1) it does not consider grade blending, (2) it does not control the risk distribution for the production target, (3) the optimality of the method cannot be guaranteed, (4) the technique is complex and difficult to apply and (5) finally, in order to get reasonable results many parameters need to be chosen carefully.

Net present value, ore tonnage, head grade, stripping ratio, amount of final production and annual target production are output parameters that Koushavand (2014) has evaluated using two different approaches. He evaluated the impact of grade uncertainty on the output parameters of a mine production plan based on an oil sands deposit case study. Usually, drillhole data is used to calculate the values of mining blocks. However, mine planners cannot know with certainty the quantity and quality of ore in the ground. In other words, the ore cannot represent the natural local grade variability within the deposits which might lead to considerable risks if not meeting planned production targets through actual operations. They also cannot predict future metal prices and foreign exchange rates.

Abdel Sabour and Dimitrakopoulos (2011) built their work by quantifying and integrating market uncertainty related to metal prices and exchange rates into mine planning. They developed a system for mine planning selection based on multiple value statistics and cash flow characteristics integrating the value of management flexibility to react to new information. The authors take into account multiple sources of uncertainty simultaneously and integrate the flexibility to revise the ultimate pit limits based on new information. Results show that a significant difference indicating the importance of incorporating uncertainty and operational flexibility into mine designs decisions.

Groeneveld and Topal (2011) evaluated the flexibility of strategic mine design under uncertainty. They used mixed integer programming (MIP) and Monte Carlo simulation (MCS) to maximize NPV and incorporates many design options (mine, stockpile, plant and port) and multiple uncertainties (price, capital cost, operating cost, recoveries and utilization). They claimed the improvement in NPV value could go further by increasing the available flexibilities in the design in addition to other uncertainties in the model. Additionally, the authors recommend further research and model improvements be continued in the following areas: Handling of grade variability through the use of conditional simulation methods will greatly improve the power of the model. If projects are improved in a way that increases flexibility to respond to uncertainties, the mining industry will be more sustainable.

8. Stockpiling

Tabesh (2015) state that most of the proposed models incorporate mining, processing and precedence constraints and do not include grade blending and stockpiling constraints. Usually stockpiling is used in mine operations for many reasons such as blending of material, storage of over produced ore (if there is enough materials to feed the plant), storage of waste material and storage of low grade ore for future production. The stockpiled ore will be processed in later years or at the end of the mine (Groeneveld and Topal, 2011; Koushavand, 2014). At the beginning of stockpiling the material, the grade and tonnage is known but as more material is added to the stockpile the grade and the tonnage become unknown (Groeneveld and Topal, 2011). Koushavand (2014) suggests penalty value for over production which will be less in the presence of stockpiling. This means any reasonable over production based on a realization will be kept in a stockpile and will be used in subsequent periods. Groeneveld and Topal (2011) state that the possibility of a non-linear constraint increases as the material in the stockpile is unknown prior to optimization. To solve this, simulated grade bins are created in the stockpile. These grade bins have a maximum and minimum grade of material which can enter each bin. When removing material the average grade is taken from the grade or alternatively, the maximum or minimum grade limit of the bin can be used.

Currently, solving large, detailed and realistic optimization problems faster is the aim of the mining industry. According to Newman et al. (2010) recent researchers focus on integrating LTPP optimization problems rather than sub-divided approaches. Developed hardware and software will help researchers solve large-scale, nonlinear problems with uncertainties.

9. Conclusion and Limitations of Current Planning and Optimization Techniques

This paper is a review of optimization models for open pit mine planning and waste management. Many researchers have studied deterministic and uncertainty-based approaches to maximize the NPV of mining operations. There are two main approaches in dealing with the mine production planning problem. First, the ultimate pit limit is determined as well as series of pushbacks using LG algorithm with parametric analysis and then production planning is generated using mathematical programming. This is the most used strategy. Second, using genetic algorithms ultimate pit limits and production planning are determined simultaneously.

Different optimization techniques for LTPP problems are presented including Linear Programming (LP), Mixed Integer Linear Programming (MILP), Integer Programming (IP), Dynamic Programming (DP), and Goal Programming (GP).

9.1. Conclusions

Johnson (1969) introduces a Linear Programming model that considers cut-off grade, however, it has too many constraints and it extracts fractional blocks. Gershon (1983) presentes a practical Mixed Integer Programming model for block sequencing. His model requires one slope constraints per block, however, it does not consider cut-off grade and it is not suitable for large deposits. Askari et al. (2011) introduce MILP model that maximizes the NPV while meeting all operational constraints. The developed model proves to be able to handle deterministic large-scale mine production problems. Badiozamani (2014) presentes a MILP model that integrates production scheduling with waste management and in-pit tailings deposition. The model solves the large-scale problem to optimality. These models do not consider uncertainties associated with variables like grade and metal prices.

Integer Programming models are presented by many researchers. Dagdelen and Johnson (1986) present a model that does not extract fractional blocks which is the main advantage. The model of Akaike and Dagdelen (1999) considers stockpiling and cut-off grade, however, it is not suitable for large deposits and there is a difference between practical and theoretical solution. Ramazan et al. (2005), presented a model that reduces the number of binary variables, minimizes the difference between practical and theoretical solution, and maximizes NPV. The optimal solution depends on pushbacks that should be generated before scheduling and the model is not easy to apply. Caccetta and Hill (2003) introduced a model that considers all operational constraints and is suitable for medium size deposits. It does not take into account dynamic cut-off grade.

Roman, Eleveli, Underwood and Tolwinski are some researchers who presented models based on dynamic programming (Osanloo et al., (2008). Their models depict that they are practical, able to optimize the pit limit and block sequencing at the same time and they consider all operational constraints. However, they do not consider dynamic cut-off grade and are not suitable for large deposits, and most importantly optimal solution is not guaranteed.

Goal Programming technique has the capability of considering multiple material types, multiple elements, and multiple destinations. GP and MILP are suitable mathematical programming models for LTPP problems and some efforts have been made to combine them for solving industrial problems. It is known as Mixed Integer Goal Programming (MIGP). It is flexible since the planner can interact with the optimization process by trading in some goals for others. Ben-Awuah et al. (2012) and Ben-Awuah (2013) have introduced a pioneering effort in developing an integrated mathematical programming model for incorporating oil sands mine planning and waste management using mixed integer linear goal programming (MILGP) in an optimization framework. Clustering technique is used in order to reduce the number of variables used in formulating the mathematical model. Decreasing the number of variables using block clustering methods are considered powerful tools to solve LTPP problems effectively. Tabesh (2015) introduced a MILP model to maximize NPV considering technical and operational constraints in addition to stockpiling schedule. The model is able to determine the optimum stockpiling strategy and the optimum mining and processing schedule in reasonable processing time. The mining-units are block clusters. These models were developed based on deterministic optimization frameworks.

Since mining projects aim at maximizing NPV and minimizing the negative impact of uncertainties, uncertainty-based techniques to solve LTPP problems have been studied by many researchers. Grade and geological uncertainties are expected as the distance between drillholes are relatively wide. Uncertainties are classified into; in-situ grade uncertainty which is the major source of inconsistencies, technical mining specification uncertainty, such as extraction capacities and slope consideration, and economic uncertainties including capital and operating costs. The uncertainty related to input parameters can increase the difference between calculated and realized NPV. Dimitrakopoulos and Ramazan (2008) stated that Rovenscroft introduced a risk analysis model using deterministic algorithms. The model shows the impact of uncertainty, however, it cannot quantify the risk and the solution is not optimal. Dowd (1997) introduced a risk analysis model using dynamic programming. His model is able to quantify the risk, but the solution is not optimal. Dimitrakopoulos and Ramazan (2003) presented a model that use linear goal programming. Although the model generated a schedule that reduces the risk of uncertainty at the early stage of production and considers block access in production planning, it extracts fractional blocks and does not maximize the NPV.

Ramazan and Dimitrakopoulos (2004) use integer programming for their model. The model maximizes NPV considering block access. It is complicated and most importantly, the integration of grade uncertainty and production planning has not been achieved. Gody and Dimitrakopoulos (2003) presented meta-heuristics model that integrates ore body uncertainty, waste management and economic and mining considerations. The model generates optimal mining rates for life of mine. It is complicated and does not guarantee the optimal solution. Koushavand (2014) introduces a MILP model for LTPP based on grade uncertainty and considering stockpiling. He introduces a cost of grade uncertainty as a new term in LTPP problem. The model shows that grade uncertainty has linear and quadratic effects on NPV. The grade uncertainty is reduced by considering stockpiling.

9.2. Limitations

9.2.1. Incorporating Uncertainties

Uncertain input variables (especially grade) should be considered in LTPP problems. That will minimize the difference between theoretical and actual NPV, and will result in a high degree of confidence for mining projects. Comprehenive models that consider the impact of grade uncertainty on stockpiling and cut-off grade optimization in LTTP problems must be developed.

9.2.2. Integrating More Areas in the LTPP

The integration of more areas in open pit mine planning will reduce the gap in the current literature. Maximization of NPV, solid waste management, minimization of dyke construction and tailings disposal costs, minimization of material handling costs for reclamation, and stockpiling materials that are below cut-off grade for limited duration are all areas that can be considered to improve the mine planning process and the performance of the models.

9.2.3. Solving LTPP and Ultimate Pit Limit Problems Simultaneously

Current approaches are still incapable of solving LTPP and ultimate pit limit problems at the same time. The effect of time on ultimate pit limit has not been considered properly. According to some researches meta-heuristic approaches such as genetic algorithms and simulated annealing can be useful for solving these combined LTPP problems.

10. References

[1] Abdel Sabour, S. A. and Dimitrakopoulos, R. (2011). Incorporating Geological and Market Uncertainties and Operational Flexibility into Open Pit Min Design. *Journal of Mining Science*, *47* (2),

[2] Akaike, A. and Dagdelen, K. (1999). *A strategic production scheduling method for an open pit mine*. in Proceedings of In Proceedings of 28th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, Colorado School of Mines, Littleton, pp. 729-738.

[3] Askari-Nasab, H. (2006). Intelligent 3D interactive open pit mine planning and optimization.Thesis, University of Alberta, Edmonton, Pages 167.

[4] Askari-Nasab, H. and Awuah-offei, K. (2009). Mixed integer linear programming formulations for open pit production scheduling. University of Alberta Edmonton, Research Report, 1, paper Document Number, pp. 8-38.

[5] Askari-Nasab, H., Awuah-Offei, K., and Eivazy, H. (2010). Large-scale open pit production scheduling using mixed integer linear programming. *International Journal of Mining and Mineral Engineering*, *2* (3), 185-214.

[6] Askari-Nasab, H., Pourrahimian, Y., Ben-Awuah, E., and Kalantari, S. (2011). Mixed integer linear programming formulations for open pit production scheduling. *Journal of Mining Science*, *47* (3), 338-359.

[7] Badiozamani, M. M. (2014). An integrated optimization model for strategic open-pit mine planning and tailings management.Thesis, University of Alberta, Edmenton, Pages 142.

[8] Barbakh, W. A., Wu, Y., and Fyfe, C. (2009). Non-standard parameter adaptation for exploratory data analysis. *Springer*, *249* 223.

[9] Ben-Awuah, E. (2013). Oil sands mine planning and waste management using goal programming.Thesis, University of Alberta, Edmenton, Pages 167.

[10] Ben-Awuah, E. and Askari-Nasab, H. (2011). Oil sands mine planning and waste management using mixed integer goal programming. *International Journal of Mining, Reclamation and Environment*, *25* (3), 226 -247.

[11] Ben-Awuah, E., Askari-Nasab, H., and Awuah-offei, K. (2012). Production scheduling and waste disposal planning for oil sands mining using goal programming. *Journal of environmental informatics, International society for environmental information sciences*, *20* (1), 20-33.

[12] Bley, A., Boland, N., Fricke, C., and Froyland, G. (2010). A strengthened formulation and cutting planes for the open pit mine production scheduling problem. *Computers and operations research*, *37* (9), 1641-1647.

[13] Boland, N., Dumitrescu, I., Froyland, G., and Gleixner, A. M. (2009). LP-based disaggregation approaches to solving the open pit mining production scheduling problem with block processing selectivity. *Computers and Operations Research*, *36* (4), 1064-1089.

[14] Boratynec, D. J. (2003). Fundamentals of rapid dewatering of composite tailings.Thesis, University of Alberta, Edmonton, Pages 267.

[15] Caccetta, L. and Giannini, L. M. (1990). *Application of operations research techniques in open pit mining*. in Proceedings of Asian-Pacific Operations Research: APORS'88, Elsevier Science Publishers, Byong-Hun Ahn, pp. 707- 724.

[16] Caccetta, L. and Hill, S. P. (2003). An application of branch and cut to open pit mine scheduling. *Journal of Global Optimization*, *27* (2-3), 349-365.

[17] Chanda, E. K. C. and Dagdelen, K. (1995). Optimal blending of mine production using goal programming and interactive graphics systems. *International Journal of Mining, Reclamation and Environment*, *9* (4), 203-208.

[18] Cheremisinoff, N. P. (2003). *Handbook of solid waste management and waste minimization technology.* Elsevier Science, New York, Second ed, Pages 477.

[19] Chicoisne, R., Espinoza, D., Goycoolea, M., Moreno, E., and Rubio, E. (2012). A new algorithm for the open-pit mine production scheduling problem. *Operations Research*, *60* (3), 517-528.

[20] Clark, K. A. (1939). The hot water method for recovering bitumen from bituminous sand. in *Sullivan Concentrator*. Alberta: Alberta Research Council, Edmonton

[21] Clark, K. A. and Pasternack, D. S. (1932). Hot water separation of bitumen from Alberta bituminous sand. *Industrial & Engineering Chemistry*, *24* (12), 1410-1416.

[22] Dagdelen, K. and Johnson, T. (1986). *Optimum open pit production scheduling by Lagrangian parameterization*. in Proceedings of 19th application of computers and operations research in the mineral industries (APCOM) symposium, USA, pp. 127-141.

[23] Datamine Corporate Limited (2008). NPV Scheduler. Ver. 4,

[24] Denby B. and Schofield D. (1994). Open-pit design and scheduling by use of genetic algorithms. *Transactions of the Institution of Mining and Metallurgy*, *Section A: Mining Technology 103:A21-A26*

[25] Dimitrakopoulos, R. and Ramazan, S. (2003). Managing risk and waste mining in long-term production scheduling of open pit mine. *SME Transactions Annual Meeting & Exhibit* 24-26.

[26] Dimitrakopoulos, R. and Ramazan, S. (2008). Stochastic Integer Programming for Optimizing Long Term Production Schedules of Open Pit Mines: Methods, Applications and Value of Stochastic Solutions. *Mining Technology*, *117* 155-160.

[27] Dowd, P. A. (1997). Risk in minerals projects: analysis, perception and management. *Transactions of the Institution of Mining and Metallurgy, Section A-Mining Industry, 106* A9-A18.

[28] Dunn, J. C. (1973). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *Journal of Cybernetics*, *3* (1973), 32-57.

[29] Esfandiri, B., Aryanezhad, M. B., and Abrishamifar, S. A. (2004). Open pit optimization including mineral dressing criteria using 0-1 non-linear goal programming. *Transactions of the Institutions of Mining and Metallurgy: Section A*, *113* (1), 3-16.

[30] Fauquier, R., Eaton, T., Bowie, L., Treacy, D., and Horton, J. (2009). In-pit dyke construction planning. in *Shell Upstream Americas, Ft. McMurray*, pp. 15.

[31] Feng, L., Qiu, M., -H., Wang, Y., -X., Xiang, Q., -L., Yang, Y., -F., and Liu, K. (2010). A fast divisive clustering algorithm using an improved discrete partics warm optimizer. *Pattern Recognition Letters*, *31* (11), 1216–1225.

[32] Gemcom Software International (2012). Whittle strategic mine planning software. Ver. 4.4, Vancouver.

[33] Gershon, M. E. (1983). Optimal mine production scheduling: evaluation of large scale mathematical programming approaches. *International Journal of Mining Engineering*, *1* (4), 315-329.

[34] Gershon, M. E. (1987). An open pit production scheduler: algorithm and implementation. in *Mining Eng.*, vol. XX, pp. 793 – 796.

[35] Gholamnejad, J. and E., M. (2012). A New Mathematical Programming Model for Long-Term Production Scheduling Considering Geological Uncertainty. *The Journal of the Southern African Institute of Mining and Metallurgy*, *112*

[36] Godoy, M. and Dimitrakopoulos, R. (2003). Managing risk and waste mining in long-term production scheduling of open-pit mines. *SME Transactions 316* (3), 43-50.

[37] Groeneveld, B. and Topal, E. (2011). Flexible open-pit mine design under uncertainty. *Journal of Mining Science*, *47* 212-226.

[38] Hannan, E. L. (1985). An assessment of some criticisms of goal programming. *Computers and Operations Research*, *12* (6), 525-541.

[39] Hochbaum, D. S. and Chen, A. (2000). Performance analysis and best implementations of old and new algorithms for the open-pit mining problem. *Operations Research*, *48* (6), 894-914.

[40] Jardine, G. H. and Evans, B. J. (1989). *CAD-approach to mine planning and production scheduling in surface mines*. in Proceedings of 21st APCOM Symp, pp. 499-505.

[41] Johnson, S. (1967). Hierarchical clustering schemes. *Psychometrika*, *32* (3), 241-254.

[42] Johnson, T. B. (1969). *Optimum open-pit mine production scheduling*. in Proceedings of 8th International Symposium on the Application of Computers and Operations Research in the Mineral Industry, Salt Lake City, Utah, pp. 539-562.

[43] Koushavand, B. (2014). Long-Term Mine Planning in Presence of Grade Uncertainty.Thesis, University of Alberta, Edmonton, AB., Canada,

[44] Laurich, R. (1990). *Planning and design of surface mines.* Baltimore, 2nd ed, Pages 1206.

[45] Lerchs, H. and Grossmann, I. F. (1965). Optimum design of open-pit mines. *Canadian mining and metallurgical bulletin*, *58* 17-24.

[46] Liang, F. and Lawrence, S. (2007). *A goal programming approach to the team formation problem.* University of Colorado, Pages 8.

[47] MacQueen, J. (1967). *Some methods for classification and analysis of multivariate observations*. in Proceedings of Fifth Berkeley Symposium on mathematical statistics and probability, University of California Press,

[48] Martinez, M. and Newman, A. (2011). Using decomposition to optimize long- and short-term production planning at an underground mine. *European journal of operations research*, *211* (2011), 184-197.

[49] McFadyen, D. (2008). Alberta Regularity. Calgary, AB. Canada, pp. 14.

[50] Newman, A., Rubio, E., Caro, R., Weintraub, A., and Weintraub, A. (2010). A review of operations research in mine planning. *Interfaces*, *40* (3), 222-245.

[51] Osanloo, M., Rashidinejad, F., and Rezai, B. (2008). Incorporating Environmental Issues into Optimum CutOff Grades Modeling at Porphyry Copper Deposits. *Resources Policy*, *33* (4), 222-229.

[52] Ramazan, S. (2007). The new fundamental tree algorithm for production scheduling of open-pit mines. *Europen journal of operational research*, *177* (2), 1153-1166.

[53] Ramazan, S., Dagdelen, K., and Johnson, T. B. (2005). Fundamental tree algorithm in optimizing production scheduling for open pit mine design. *Transactions of the Institutions of Mining and Metallurgy: Section A*, *114* (1), 45-54.

[54] Ramazan, S. and Dimitrakopoulos, R. (2004). *Recent applications of operations research and efficient MIP formulations in open pit mining*. in Proceedings of SME Annual Meeting, SME Cincinnati, Ohio, pp. 73-78.

[55] Rashidinejad, F., Osanloo, M., and Rezai, B. (2008). An Environmental Oriented Model for Optimum Cut-Off Grades in Open Pit Mining Projects to Minimize Acid Mine Drainage. *Int. J. Environ. Sci. Tech.*, *5* (2), 183-194.

[56] Rodriguez, G. D. R. (2007). Evaluating the impact of the environmental considerations in open pit mine design.Thesis, Colorado School of Mines, Golden, Pages 160.

[57] Runge Limited (2009). XPAC Autoscheduler. Ver. 7.8,

[58] Scott Dunbar, W. (2012). *Basics of Mining and Mineral Processing.* University of British Columbia,

[59] Singh, G. (2008). *Environmental impact assessment of mining projects*. in Proceedings of International conference on TREIA-2008, Nagpur, India,

[60] Tabesh, M. (2015). Aggregation and Mathematical Programming for Long-Term Open Pit Production Planning.Thesis, University of Alberta, Edmonton, AB., Canada,

[61] Underwood, R. and Tolwinski, B. (1998). A mathematical programming viewpoint for solving the ultimate pit problem. *European Journal of Operational Research*, *107* (1), 96-107.

[62] Whittle, J. (1989). The facts and fallacies of open pit design. Ver. North Balwyn, Victoria, Australia.

[63] Zeleny, M. (1980). Multiple objectives in mathematical programming: Letting the man in. *Computers and Operations Research*, *7* (1-2), 1-4.

Discrete Event Simulation of Truck-Shovel Operations in Open Pit Mines

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Abstract

Discrete event simulation is a powerful tool that has been used by many researchers to study complex systems and analyze the performance indicators for the current system versus proposed modifications and expansion scenarios. In the paper, we take a holistic approach at an open pit mining operation by incorporating the truck-shovel operations, road networks, processing plants, stockpiles, equipment failures, maintenance and capacity changes into a simulation model. The model in developed in Arena simulation software and is complemented by Matlab, Excel, Word and VBA modules to offer a complete flexible package that can be rebuilt and reused overtime by operation managers. Our framework takes production and maintenance schedules, haul road network, truck list and allocation strategy, shovel list, operation control parameters, and other probability distribution functions as inputs through spreadsheets and produces the reports required for analyzing the system performance and comparing expansion and modification scenarios. This paper explains all the steps required to develop and implement a simulation model by automating the procedure through programming and flexible model building and concludes by presenting normalized operation versus simulation statistics and plots to show the accuracy and reliability of our simulation model.

Keywords

Discrete Event Simulation, Open Pit Mining, Truck-Shovel Operation, Dispatching

1. Introduction

Accurate prediction based timely decisions result in improved outcomes for organizations. Simulation techniques have evolved over the years to accurately model the systems and predict on outcomes for user desired scenarios. Accurate modeling of such simulation models is essential for reliable and confident decision making involving huge capital investments. This paper presents the development, implementation, and validation of an industrial strength simulation model of a large scale open pit mine with truck-shovel operations.

The application of simulation in mining can be traced back to around 1940. With the evolution and familiarization, simulation techniques have been widely accepted as the powerful tool for modeling

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the processes and analyzing the system responses with changing parameters of the system; and in-turn optimizing the system performance. Sturgul (2001) describes the importance of simulation in mining and describes GPSS/H and SIMAN based ARENA as the two most commonly used discrete event simulation languages in this field. Researchers have used simulation for a wide number of mining applications. Ataeepour and Baafi (1999), Forsman et al. (1993), Kolonja and Mutmansky (1994) and many others have used simulation to analyze the impact of dispatching strategies on the mining operations. Awuah-Offei et al. (2003) used simulation to determine the optimal truck and shovel requirements in a mine. Upadhyay et al. (2013) used simulation to determine optimum truck requirements in continuous surface mining systems. Simulation models developed by Sturgul and Eharrison (1987), Peng et al. (1988), and Forsman et al. (1993) among others are all developed for specific mining systems due to the nature of mining operations.

Simulation model have also been used in conjunction with external engines for decision making purposes. Fioroni et al. (2008) uses simulation in conjunction with a mixed integer linear programming model to reduce mining costs by optimal production planning. Yuriy and Vayenas (2008) use discrete event simulation in conjunction with a reliability assessment model based on genetic algorithms to analyze the impact of equipment failures on production, mechanical availability and equipment utilizations. In another paper Hodkiewicz (2010) provide a broad review of simulation modeling in mining and describe the applicability of the simulation modeling in understanding the impact of preventive and corrective maintenance on the production. Raj et al. (2009) provides a critical review of the application of simulation techniques for production optimization in mining.

The researchers, through various simulation models, have proved the power of simulation and in-turn proved the opportunity to improve the mining operations through simulation. Most literature on the application of simulation modeling in mining focuses on the aspect of robustness of simulation and do not detail the development of the models as such. The literature reviewed does not talk about the ease of application and re-usability of the models over time.

The development of a simulation model involves four major stages: 1) data analysis and distribution fitting, 2) simulation modeling, 3) verification and validation and 4) experimental design of scenarios and analysis. One of the major objectives set for this project was to develop a validated simulation model which is flexible and reusable over time within the given mining system. To achieve the objectives set for this project all the four major stages discussed above have been completed by designing user friendly interfaces which enable the user to recreate the model for the same mining system over time.

The objective of this project is to create a reliable simulation tool of the truck-shovel operation based mining system in conjunction with the downstream processing plant assets to be used in large scale open pit mining operations as a planning tool in the presence of uncertainty. The key features desired in the model are:

- A logic within the simulation model for truck dispatching to replicate the fleet management system's dispatch algorithm (Leica Geosystems Mining; Modular Mining Systems Inc.; Wenco International Mining Systems Ltd.),
- Assign truck speeds on the haul road network based on the rimpull curve (Bonates, 1996) configuration of trucks; and haul road gradients and rolling resistances of the road segments,
- Truck movements on the haul roads maintaining a safe following distance leading to platoon formations and traffic congestions,
- Incorporate a short-term production schedule as the input into the simulation model,
- Model the effect of shift change and coffee breaks on the production,
- Model the effect of seasons and weather events on the production,

- Incorporate various types of failures and preventative maintenance of equipment,
- Model the material flow in and out of the processing plants,
- Model uptime and downtime of crusher and downstream assets,
- Model stockpiles as a buffer balancing the discrete mine operation with the continuous processing plant operation.

Including the mine haul road network and moving the trucks based on haul road characteristics, safety distances, and yielding the right of way at the intersections on the haul roads brings this simulation model closer to reality, where the model provides further insights on the traffic congestions and its impact on production. This is one of the key features missing from the simulation models found in the literature, which fail to account for the platoon formations on the haul roads hampering production operations significantly.

A truck dispatching logic is another key addition in this model which helps reproduce dispatching decisions similar to those made in the real time mining operations by Fleet Management Systems (Leica Geosystems Mining; Modular Mining Systems Inc.; Wenco International Mining Systems Ltd.).

A simulation model on such a large scale has to be flexible and user friendly to run different scenarios and analyze results easily. The simulation model is therefore created in Arena (Rockwell Automation) taking all model inputs from an external configuration file. A VBA interface in Arena has been created to rebuild the model completely in case the haul road network, type and number of trucks and shovels, the production schedule, or any other input parameter of the mine changes.

Apart from modeling the mine and processing plant systems, it is essential to analyze the outputs easily and quickly. The simulation model generates large amount of data, which is stored in a database in the same format as the mine fleet management database (Leica Geosystems Mining; Modular Mining Systems Inc.; Wenco International Mining Systems Ltd.). To generate and analyze the results quickly a Matlab GUI is created which sends queries to the database, generates and plots the descriptive statistics, histograms, and quantile-quantile plots of data versus simulation results and creates a word file report of the results. The whole simulation tool is created by keeping its implementation as simple as possible, keeping in mind the needs of the user with no prior knowledge of simulation modeling to analyze the impact of desired scenarios on the overall system operations over time.

The rest of the paper is structured as follows: the next section describes the problem definition, scope and limitations of the model developed in this paper, followed by the methodology section which presents a broad overview of the approach adopted to achieve the objectives of the project. The section on “simulation” then presents the logic adopted in developing the simulation model. The model implementation, validation, and results are then presented followed by conclusions and future work directions.

2. Problem Definition

2.1. System

The system being modeled is a large scale open pit mine operation consisting of shovels, trucks, processing plants, stockpiles, and waste dumps along with the haul road network of the mine.

2.2. Objective

The objective of the project presented in this paper is to develop a simulation model of the system, validate it against the historical data and use it as a planning tool to run new scenarios to analyze the impact of new mine layout, haul road network, equipment type and size on the major key performance indicator of the open pit mine and processing plant system.

2.3. Scope and limitations

Although the flexibility included within the model makes it reusable over time within the same mining system; due to the nature of the simulation models and the input probability density functions based on historical data, the model is not a general tool. Modifications are required to the model to be tailored to other mining operations. Model, although, is capable to handle changes for the same mining system through the external input file, without changing the model. Major changes that can be made using the external input file include:

- Haul road network
- Probability density functions,
- Maintenance schedules,
- Number and characteristics of trucks and shovels,
- Plant characteristics and downstream flow rates,
- Truck allocation strategy to be used for truck dispatching by fleet management system.

3. Methodology

3.1. Framework

We needed to develop a framework to handle the historical dispatch, failure, and preventive maintenance data analysis outcome and probability distributions, and to set and modify model parameters and generate the reports. Moreover, the level of reporting required was beyond the built-in capabilities of Arena. Therefore, various codes and databases were developed to perform each task. A brief explanation of the framework pieces is presented here.

- Database: the historical dispatching and failure required a database in order to hold the information and provide fast and flexible access to perform analysis on different subsets of data. On the other hand, since the project required complex and customized reports, we decided to create a database import every cycle of the truck-shovel operation, failures and maintenance records and plant production from the simulation model into a database. Therefore, Microsoft SQL database engine was used with four pairs of tables for original and simulation data. The tables hold the dispatch records, failure and maintenance, and processing plants hourly production.
- Matlab®: Matlab R2015b (The MathWorks) is used for performing statistical analysis on historical and simulation data. Various functions and GUIs are developed to retrieve subsets of data from the historical and simulation databases and perform statistical analysis.
- Excel: we needed a GUI to input parameters for creating and controlling the simulation model which is easy to manipulate. Therefore, we used Excel workbooks with macros to create a GUI for setting model input parameters that are read into Arena and used for generating the model and setting operation parameters.
- Word: we have automated the report generation process by developing macros in Microsoft Word to import graphs including histograms, quantile-quantile plots, and descriptive statistics to generate desired reports for historical data and simulation outcome analysis.

3.2. Data Analysis

Statistical analysis of the historical and simulation data is a very important part of any simulation project. The analysis has to be performed on the historical dispatch and failure data in order to obtain probability distributions and determine valid boundaries for control and output parameters. On the other hand, the simulation results have to be statistically analyzed to be able to validate the model; and afterwards, perform meaningful and reliable comparisons of different expansion and modification scenarios. Therefore, we developed Matlab codes to retrieve data from historical and simulation databases with various groupings on the shovels, trucks, material groups and destinations, time intervals and operations crews. We have used these functions to plot histograms and create statistical summaries of more than 200 combinations of data fields and groups. The historical dispatch data analysis is summarized in Table 1.

Table 1.Statistical Analysis for Historical Dispatching Data

	Groups			Histogram	Probability Distribution
	Truck Type	Shovel Type	Destination		
Load Tonnage	×	×		×	×
Empty Distance			×	×	
Full Distance	×		×	×	
Empty Velocity	×			×	×
Full Velocity	×			×	×
Empty Haul Time	×		×	×	
Full Haul Time	×		×	×	
Spot Time	×	×		×	×
Loading Time	×	×		×	×
Hang Time		×		×	
Queue Time				×	
Dump Time	×		×	×	×

In order to model the truck, shovel and plant facility failures we grouped multiple failure codes to have enough records of historical data for distribution fitting and also to decrease the number of failures defined in the model. However, we kept the groups within failure categories to be able to model and report different categories of downtime independently. On the other hand, multiple maintenance schedules are modeled with fixed uptime and downtime for trucks, shovels and plant facilities independent from the failures and report under their designated category. The time categories for the equipment are presented in Table 2.

Table 2. Equipment Time Categories

ID	Category	Trucks	Shovels	Plant Facilities
1	Work	×	×	×
2	Operations Delay	×	×	
3	Operations Standby	×	×	
4	Short Down	×	×	
5	Down Service	×	×	×
6	Down Technical	×	×	×
7	Down Waiting	×	×	
8	Out of System	×	×	

3.3. Fitting distributions

As mentioned earlier, we developed multiple Matlab functions to retrieve subsets of data and fit probability distributions. However, since the distributions are going to be used in Arena we developed another function to retrieve the values and write them to a text file. Arena Input Analyzer is then used to import the text file and determine fitting probability distributions for each set of values. The two methods work in parallel and provide an ability to have multiple distributions for one parameter and choose the one that fits data better theoretically and statistically. Moreover, we created a function to create Empirical probability distributions wherever finding a theoretical distribution is not possible. More than 1300 probability distributions were modeled as input parameters into the simulation model.

3.4. Building the model

The simulation model consists of two parts: the fixed and the dynamic parts. The fixed part of the model is built in Arena and controls the logic of the model and all the modules required for simulation. On the other hand, we developed a VBA procedure in order to dynamically build the rest of the simulation model from a configuration file. Our code reads the list of shovels, trucks, mining polygons, road network and all the required distributions and settings from an Excel configuration file and updates the corresponding resources, transporters, variables, expressions and module settings in Arena. Therefore, we have the flexibility to change the model without touching the main logic. Moreover, this provides the option to change the model without having the modeling knowledge necessary to build a model in Arena. The details of fixed and dynamic parts of the model are presented in the fourth section of the paper.

3.5. Validation and scenario evaluation

As mentioned earlier, we decided to use the database for generating validation and scenario evaluation process. To do so, we need to save every cycle of the truck-shovel operation, equipment failures and plant productions into the database. Arena provides an option to directly write into SQL databases using ADO method; however, the procedure is time consuming as it has to open and close a connection to the database for every record. Therefore, we write all the simulation records into a text file and import them into SQL after the simulation is over. The Microsoft SQL bulk import and export command prompt tool is called from a VBA function to automatically import the results into the database. The bulk import is the fastest way of importing large text files into SQL database.

After importing simulation data into SQL database, post-processing stored procedures are called to clean up the simulation results and make them ready for reporting. Three sets of Matlab functions are developed to validation the results and evaluate various scenarios. The first set compares one replication of simulation results to the historical data by creating field by field comparison reports and graphs as shown in section 5.The reports include summaries of production and operation KPIs as well as field by field comparisons. The second set compares multiple replications of simulation results to the historical data through comparing the historical recorded values to replication means and half widths calculated from multiple replications. Report and graph examples are presented in sections 5.1 and 5.2. The third set is developed to compare multiple replications from two simulation scenarios. The codes are developed to compare the means and half widths from two different sets of simulation replications.

4. Simulation

The most important step in building a simulation model is the conceptual modeling. This step of the procedure helps us understand the model without getting into the details of modeling and is independent from the software and modeling environment we are planning to use. We have broken down the system into various sub-models and built conceptual models in different resolutions in different stages of modeling. Most of these conceptual models cannot be presented here due to confidentiality of the project. However, high level models, which are related to processes shared by all truck-shovel operations, are presented in this section. The high level conceptual model of the whole operation is presented in Fig. 1. Details of modeling and some of the sub-models will follow in the upcoming sections.

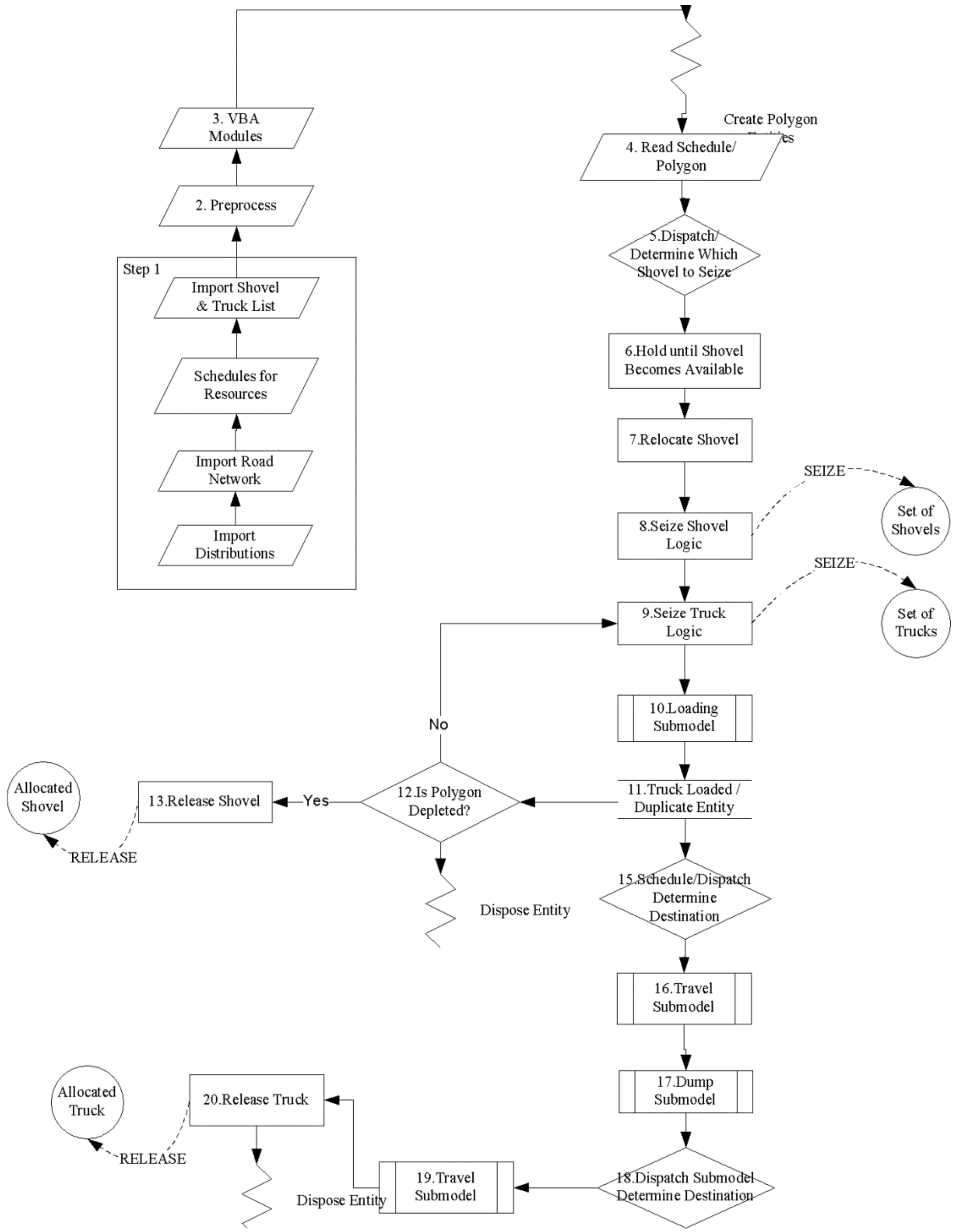

Fig. 1. Conceptual Model

4.1. Production schedule

One of the most important parts of a truck-shovel operation simulation is the production schedule. The production schedule is an input into the simulation model and can be used to validate the model against the historical data and to evaluate various scenarios of moving shovels from ore to waste and vise versa, and of changing mining directions and lead and lag in bench mining. The production schedule in our model is a sorted list of mining polygons with polygon center coordinates, destinations, material types and tonnages, grade and contaminant values, and assigned shovel IDs. However, the model is capable of importing polygon precedence and assigning shovels to mining polygons when they are available. Although the destination of material extracted from each polygon is determined in the production schedule, the dump location (e.g. hopper) is decided in the simulation model by an embedded dispatching logic.

4.2. Travel

Truck haulage is a critical part of the mining system which proves to be a bottleneck in most production operations. The major problem is posed by the platoon formations on the haul road segments which significantly affects the truck travel times and thus hampers production. Thus it is necessary to capture such truck interactions in the simulation. The major reason of such truck interactions is the difference in speed of trucks of different types and also intersections at various points of the haul road network. Such interactions are very common in mixed fleet systems where speed of different truck types differ significantly on different haul road conditions. To account for these truck interactions and to capture the realistic truck travel times, the simulation must incorporate the haulage road network of the mine and impart truck speeds based on the haul road conditions.

To build the haul road network of the mine, the road network poly-lines of the mine are exported from any design software and written as segments in the configuration input file using a GUI interface built in Matlab. The GUI provides the capability to merge the segments, based on the gradient and length tolerance, to reduce the total number of segments created in Arena if the road network of the mine is very large. The VBA interface in Arena is then used to create the haul road network as connected road segments. The configuration file also contains the haul road gradients and rolling resistances of the road segments to assign appropriate speeds to trucks.

The truck travel is modeled as presented in Fig. 2. Trucks are moved on the network through the segments by imparting speeds based on the rimpull curve characteristics of the truck; and gradient and rolling resistance of the road segment. When a truck reaches to the start of a segment, its sampled flat haul speed is multiplied with a speed factor based on the total resistance of the next segment and the rimpull characteristic of the truck as the speed of the truck on the next segment.

To model the safe following distance between trucks and restricting overtaking, the trucks are modeled as guided path transporters and haul road network is built as network in Arena. The network in Arena is made by using the segments as network links consisting of zones. The truck movements on these links occur by seizing the next zone and releasing the occupied zones. By setting the zone control rule as “Start”, Arena allows any trailing truck to seize the next zone only when it has been released by the leading truck. This enables the model to restrict overtaking of trucks. To model a safe following distance, the zone lengths are set as the summation of average truck length and the safety distance. Thus a trailing truck will have to stop at the safety distance if the leading truck stops.

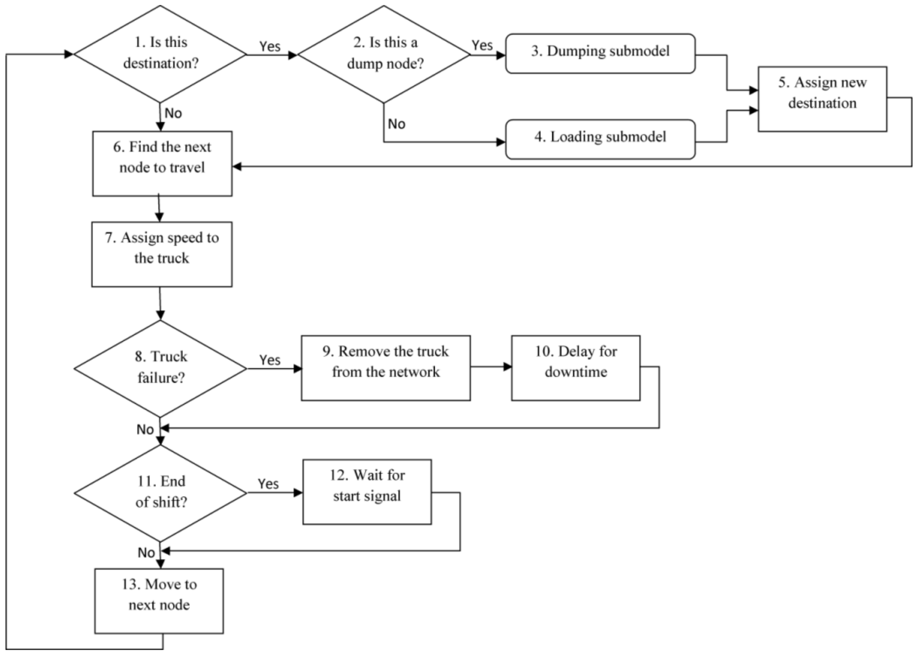

Fig. 2. Haulage system logical flow diagram

Modeling haulage system using guided path transporters and network links brings the travel model very close to reality. This type of modeling can be considered to be closer to micro-simulation approaches. One of the major drawbacks posed by this approach is the longer run times of the simulation model. Another parallel approach is therefore created in Arena which although restricts overtaking of trucks, does not guaranty safety distance between trucks. Replacing guided path transporters and network links with free path transporters and distances in Arena, reduces the run time of the model significantly. The major problem with free path transporters is that it does not move the trucks zone by zone and thus allows any overtaking based on speed of trucks. This is controlled by adjusting the speed of trucks on the segments so that a trailing truck does not reach the end of the segment before its leading truck and thus restricting overtaking. A comparison between the two approaches shows that run time with the free path approach is significantly lower than the guided path approach and the production results are marginally higher with the free path approach.

4.3. Season

The effects of season changes have to be considered in the simulation model. Therefore, we divided the historical data into two seasons while performing statistical analysis and determined which parameters require separate distributions for the summer and winter. On the other hand, a variable in simulation model changes based on simulation time and makes simulation modules choose the proper distribution based on the current season.

4.4. Truck and shovel downtimes

As mentioned in the previous sections, we grouped various failures for trucks and shovels within the defined categories and fitted distributions on the TBF (time between failure) and TTR (time to repair). The shovels are defined as the resources in the Arena model. Therefore, we can use the resource schedules and failures modules in Arena. However, using the built-in modules removes the ability to collect independent statistics based on failure categories. Therefore, we created a separate logic to sample TBF and TTR values for each shovel and control the maintenance schedules. The logic is presented in Fig. 3. A 1-dimensional variable is used to hold the state of each shovel to allow failure and maintenance downtime overlaps. We are holding the failure entity in a queue if the shovel is already inactive due to other failures or maintenance. Therefore, the sampled total downtime would be preserved by postponing the failure until the shovel becomes available. A similar logic is implemented for the trucks with another 1-dimensional state variable. However, since the trucks are modeled as transporter modules in Arena, they cannot be set to inactive through a module. Therefore, we check the truck state variable in every intersection of the road network and take it out of the network if failed. The logic for truck failure modeling is presented in Fig. 4.

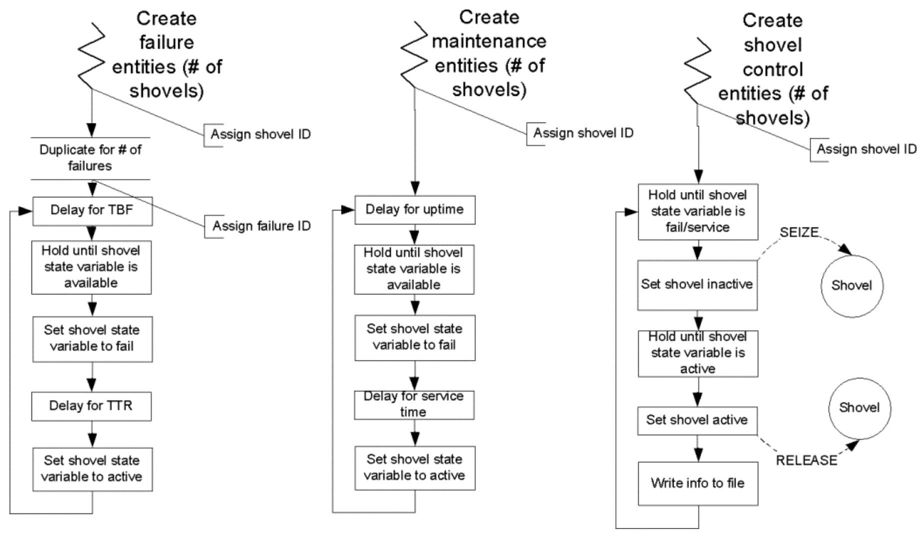

Fig. 3.Shovel Failure Logic

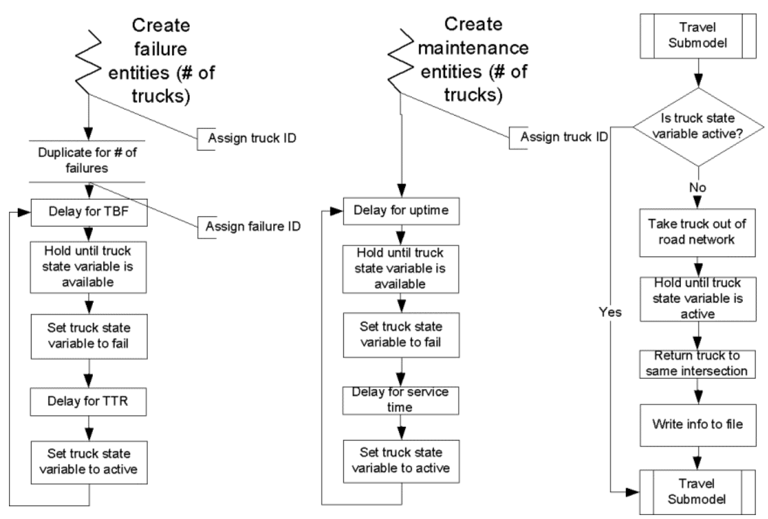

Fig. 4. Truck Failure Logic

4.5. Shift change, coffee break and weather events

Shift changes and coffee breaks are events that happen on a regular basis compared to failures and affect all the trucks and shovels simultaneously. However, how long they take can be determined by a probability distribution. On the other hand, weather events happen randomly but affect all the trucks and shovels. We modeled these three independently by changing state variables for all trucks and shovels when they happen. The same module explained for truck and shovel failures will set the equipment to inactive for the duration of these events.

4.6. Processing plant

Adding the processing plant to the simulation model can significantly improve the reliability of the truck-shovel simulation due to queuing for dumping at the hoppers. On the other hand, processing plants can be unavailable or be working with less than nominal capacities when failures occur on downstream assets. Therefore, we added the upstream processes of the processing plant to the simulation model to mimic the hopper capacity constraints and changes in the throughput rate. Two separate plants with seven hoppers are simulated with the initial crushers and conveyer belts. A combination of continuous and discrete modules is used to model the plants in Arena. Eleven facilities are modeled as resources to simulate failures and maintenance schedules for the plants, seven hoppers and two surge bins are modeled as tank modules with limited capacities, and eleven conveyer belts are modeled to account for variations in the throughput rates with distributions fitted on historical data. The load dumping sub-model logic is presented in Fig. 5. The processing plant details cannot be presented due to confidentiality. However, an example of how the relationships between the surge bins and conveyer belts are modeled is presented in Fig. 6.

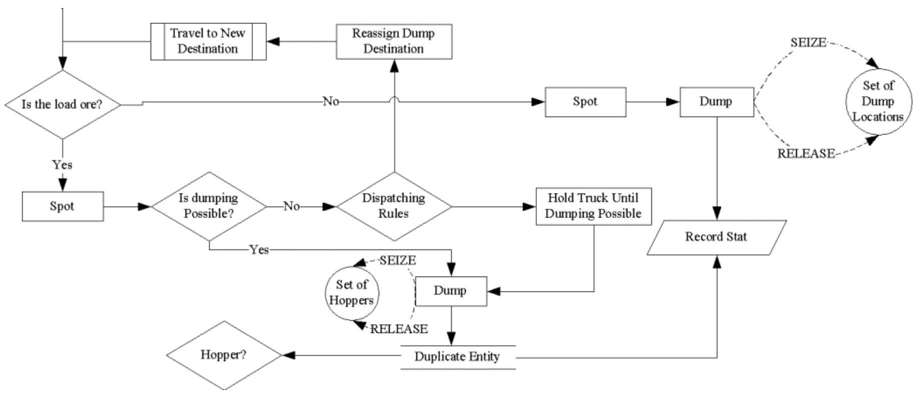

Fig. 5. Dump Submodel

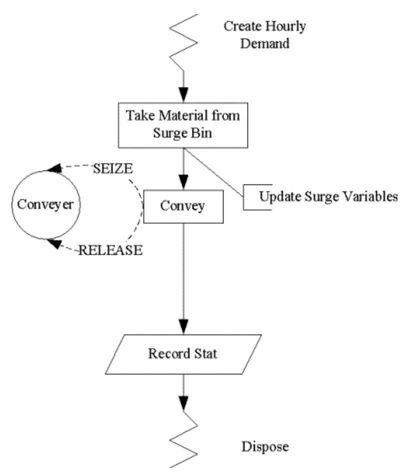

Fig. 6. Surge Bin to Conveyer Belt Logic

4.7. Dispatching

We have developed two dispatching modules in our simulation model. The first module is responsible for assigning empty trucks to shovels and the second module is responsible for determining and updating the dump location of loaded trucks. The latter works simply based on assigning trucks to the dump location currently available and with the least number of trucks on route. Therefore, in this section, we explain the procedure used to assign the empty trucks to shovels in more details.

First, we calculate the cycle time for each shovel based on the current polygon destination and average values for loading and spot times, velocities and dump times. Next, we calculate the number of trucks required for each shovel to be fully utilized. Afterwards, we assign a dispatch value to each shovel and assign the truck to the shovel with the lowest value. The dispatch value is calculated based on the following parameters:

1. Number of trucks currently assigned to the shovel divided by the number of trucks required,
2. The distance from the current location of the truck to the shovel,
3. Over-delivery of ore to the processing plants,
4. Truck to shovel type assignment probability,
5. Truck to material type assignment probability,
6. Truck to material type lock status,
7. Truck to pit lock status,
8. Current state of the shovel (i.e. active, fail and idle),
9. Maximum number of trucks allowed to be allocated to one shovel.

The first five parameters work as weighted decision making factors while the rest work as hard constraints that should not be violated by the assignment. Therefore, there are weights defined and calibrated for the first five factors to adjust the dispatching module to the reality of the operation. The first factor represents shovels' need for trucks to be fully utilized. The second factor is considered to avoid long distance assignments. Next, the past hour delivery of ore to the processing plants is compared to an adjustable threshold and will penalize ore shovels if the plant is overfed to avoid long queues at hoppers. The shovel type and material type probabilities are calculated from the historical data and can be adjusted for every truck in the system. On the other hand, the sixth and seventh factors provide the option to lock a number of trucks to a specific material type and/or pit, or to allow floating based on the current state of the operation. Moreover, we have to avoid allocating trucks to shovels that have failed or are not working due to not having any mining face available. Finally, we added an external control parameter to control the maximum number of trucks assigned to each shovel at any time during the simulation.

4.8. Warm-up time

Another important part of the simulation model is the warm-up time. We have considered ten days for the warm-up with specifically marked dummy polygons for the truck-shovel operation to get to a stable point before we start collecting statistics. The load records, failures and plant production records from the warm-up period are flagged and deleted during post-processing.

5. Results

In this section, we present the results of validating the simulation model against the historical data. We break down this section into two main parts for validating the model for three months: a) validating the model using one replication, and b) validating the model using multiple replications. The results and graphs are automatically generated by the developed Matlab codes and Excel spreadsheets.

5.1. Three-month single replication

We have setup the model based on distributions obtained from the historical data and fine-tuned the model parameters to achieve results similar to the last three months of the available data. Moreover, we created the production schedule from the historical data recorded for the same shovel in the same order of extraction. The production schedule consists of mining polygons including the warm-up polygons. The percentage difference between the simulated results and the historical data for all statistics is presented in Table 3. The actual values are omitted for confidentiality purposes. Two examples of normalized histograms of recorded and simulated parameters along with the quantile-quantile (QQ) plots are presented in Fig. 7 to Fig. 12.

Table 3. Single Replication Results

	Count	Min	Max	Range	Mean	Median	ST.Dev.	Summation
Measureton	10%	0%	0%	0%	2%	2%	-2%	0%
Empty Distance	10%	114%	-2%	-4%	-6%	-6%	9%	-9%
Full Distance	13%	101%	-5%	-7%	-1%	-1%	16%	1%
Empty Travel Time	14%	0%	0%	0%	-3%	-5%	26%	1%
Full Travel Time	13%	0%	-3%	-4%	-3%	-3%	22%	0%
Spot Time	17%	0%	2%	2%	-5%	-7%	-4%	-1%
Loading Time	12%	76%	0%	-4%	-3%	-7%	1%	1%
Dump Time	16%	0%	2%	2%	-3%	-3%	11%	2%

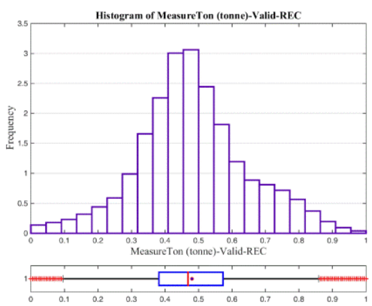

Fig. 7. Recorded Measureton

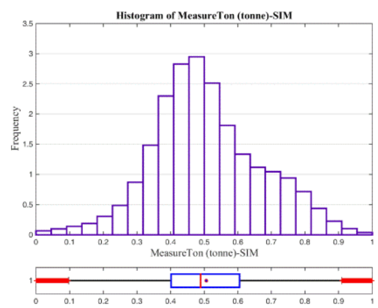

Fig. 8. Simulation Measureton

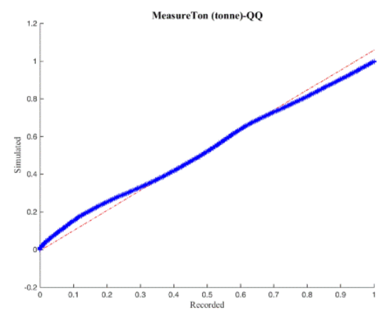

Fig. 9. Measureton QQ Plot

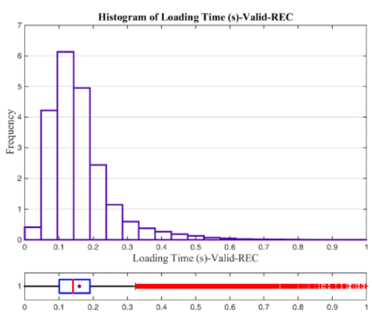

Fig. 10. Recorded Loading Time

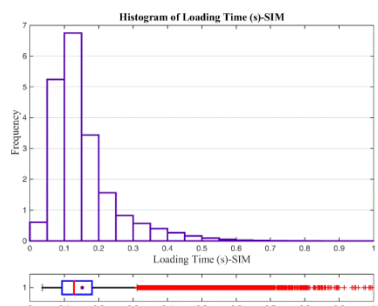

Fig. 11. Simulation Loading Time

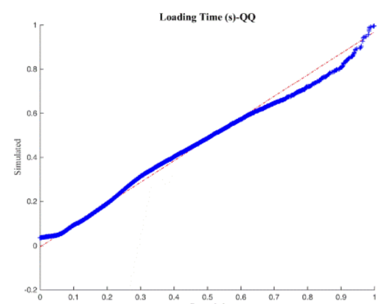

Fig. 12. Loading Time QQ Plot

In addition to the general histograms our codes create the plots and statistics grouped by truck type, shovel type and material type. We have replaced the actual truck type and shovel types with numbers. Truck tonnage values for recorded and simulated values are plotted and compared for shovel type 1 loading ore on truck type 3 in Fig. 13 to Fig. 15.

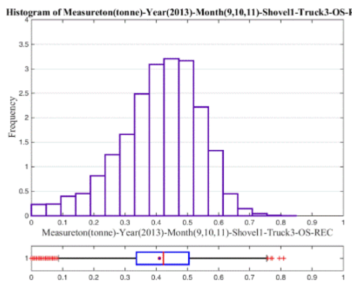

Fig. 13. Recorded Measureton

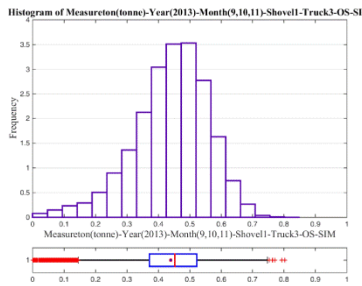

Fig. 14. Simulation Measureton

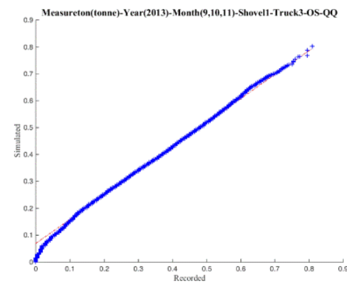

Fig. 15. Measureton QQ Plot

5.2. Three-month multiple replications

We used the same parameters from the single replication model and ran 20 replications. The production schedule is the same as the single replication and the simulation results are compared against the same set of historical records. The difference between the single-replication and multi-replication reports is in reporting the values with half widths. The half width is a statistical measure to understand the uncertainty around an output parameter. The half widths presented in the following tables and graphs are calculated based on 95% statistical confidence level. For confidentiality reasons, the simulated measures and their half widths are divided by the historical recorded value and presented as percentage. For example, the average summation mined tonnages in 20 replications is equal to the recorded summation and the 95% confidence interval for it is ±0.78% of the recorded tonnage. Some of the major validation measures and truck KPIs are presented in Table 4 and Table 5. The corresponding plots are presented in Fig. 16 to Fig. 21.

Table 4.Multiple Replication Results

	Mean	H. W.	Median	H. W.	ST.Dev.	H. W.	Summation	H. W.
Measureton	102%	0.05%	102%	0.04%	99%	0.21%	100%	0.78%
Empty Distance	93%	0.42%	93%	0.84%	108%	0.57%	90%	0.80%
Full Distance	97%	0.46%	95%	1.18%	114%	0.62%	99%	0.96%
Empty Travel Time	96%	0.51%	94%	0.66%	126%	0.68%	100%	0.82%
Full Travel Time	97%	0.40%	96%	0.61%	124%	1.34%	99%	0.84%
Spot Time	94%	0.13%	94%	0.13%	93%	0.29%	99%	0.73%
Loading Time	98%	0.31%	95%	0.21%	101%	0.88%	101%	0.66%
Dump Time	93%	1.28%	95%	0.24%	110%	5.17%	98%	1.63%

Table 5.Shovel KPI Results

	Mean	H. W.	Median	H. W.	ST.Dev.	H. W.	Summation	H. W.
Total Hours	100%	0.00%	100%	0.00%	100%	0.00%	100%	0.00%
Work	100%	1.46%	98%	1.79%	63%	4.49%	100%	1.46%
Ops Delay	106%	1.37%	104%	2.68%	54%	2.86%	106%	1.37%
Ops Standby	100%	3.36%	94%	4.15%	85%	6.89%	100%	3.36%
Short Down	78%	1.14%	84%	1.89%	30%	2.81%	78%	1.14%
Down Service	99%	9.08%	97%	24.30%	86%	4.78%	99%	9.08%
Down Technical	96%	2.95%	155%	6.13%	21%	2.05%	96%	2.95%
Down Waiting	132%	19.50%	100%	0.00%	42%	5.06%	132%	19.50%

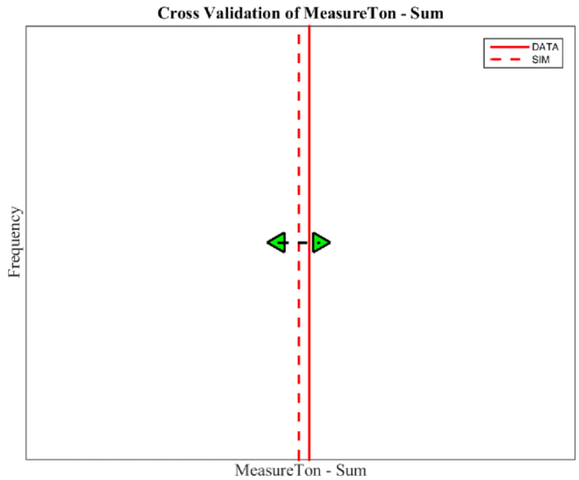

Fig. 16. Measureton Summation

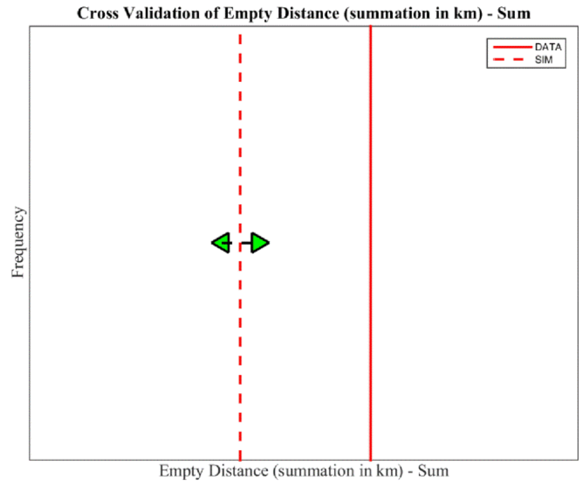

Fig. 17. Empty Distance Summation

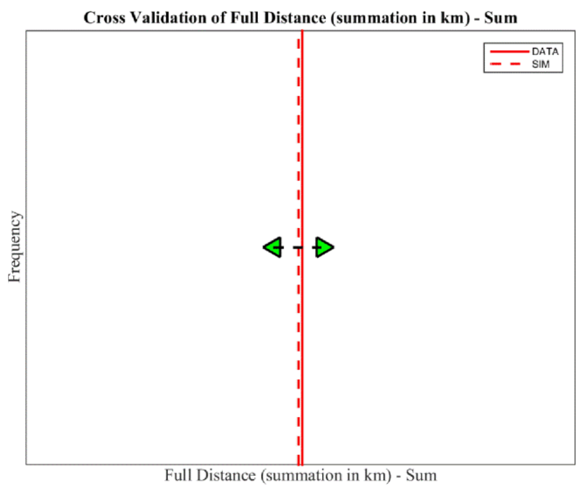

Fig. 18. Full Distance Summation

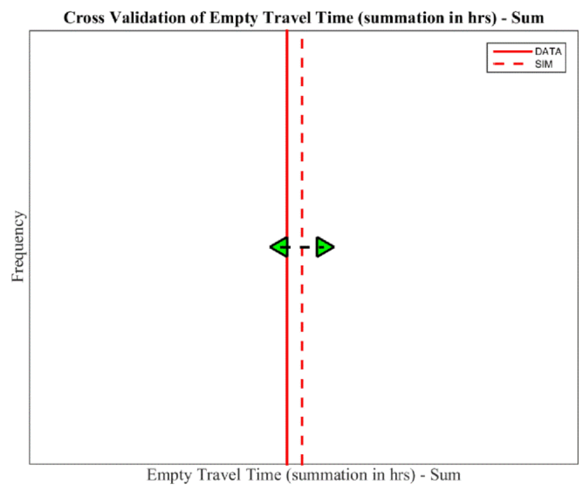

Fig. 19. Empty Travel Time Summation

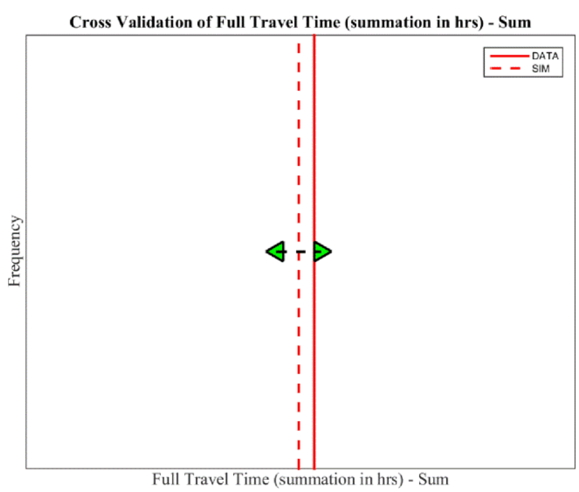

Fig. 20. Full Travel Time Summation

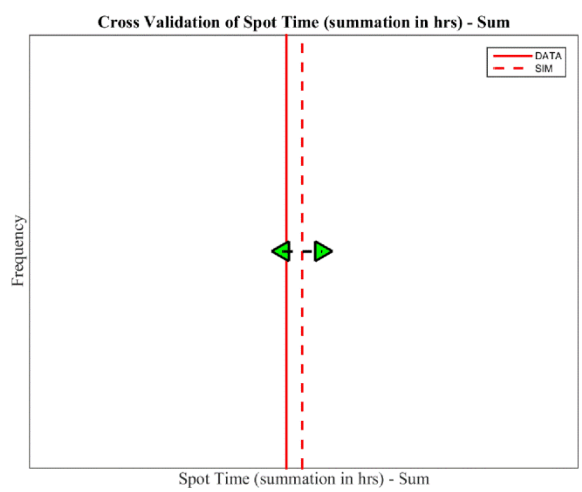

Fig. 21. Spot Time Summation

6. Conclusion and future work

Discrete event simulation is a powerful technique for studying complex systems that change states over time. Truck-shovel operation in an open pit mine is one of those complex systems that is affected by large number of uncertain parameters. Therefore, in this paper, we presented the steps to build a simulation model for an open pit mining operation. We have developed the model in Arena simulation software and used SQL databases, Matlab codes, Excel interfaces and VBA programs to create a dynamic framework to analyze the historical data and evaluate various expansion and modification scenarios. The simulation tool inputs the production schedule, road networks and other operation parameters and simulates the current operation as well as planned scenarios. Travel sub model coupled with rimpull curve characteristics of trucks and haul road characteristics enabled the model to capture realistic truck travel times and truck interactions.

In this paper, we presented the conceptual diagrams of the operation and the simulation model and the details of the modeling procedure. We showed that our model is able to mimic the current operation by comparing the statistics and histograms of the historical data and the simulation results. Moreover, we showed how we can build a confidence interval around the performance measures of the operation by running multiple replications of the simulation model in order to capture the existing uncertainty in the operation as well as proposed scenarios.

For future studies, we recommend developing more accurate dispatching modules that incorporate optimization engines to improve truck allocations. On the other hand, decreasing the runtime for the simulation model can improve the usability of the model.

7. References

[1] Ataeepour, N., & Baafi, E. Y. (1999). ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. *International Journal of Surface Mining, Reclamation and Environment, 13*(3), 125-130.

[2] Awuah-Offei, K., Temeng, V. A., & Al-Hassan, S. (2003). Predicting equipment requirements using SIMAN simulation a case study. *Transactions of the Institution of Mining and Metallurgy Section A-Mining Technology, 112*(3), A180-A184.

[3] Bonates, E. (1996). Interactive truck haulage simulation program. *Mine Planning and Equipment Selection*, 51-57.

[4] Fioroni, M. M., Franzese, L. A. G., Bianchi, T. J., Ezawa, L., Pinto, L. R., & de Miranda, G. (2008). *Concurrent simulation and optimization models for mining planning*. Paper presented at the WSC 2008.

[5] Forsman, B., Rönnkvist, E., & Vagenas, N. (1993). Truck dispatch computer simulation in Aitik open pit mine. *International Journal of Surface Mining, Reclamation and Environment, 7*(3), 117-120.

[6] Hodkiewicz, Melinda, Richardson, Steven, & Durham, Richard. (2010). *Challenges and Opportunities for Simulation Modelling Integrating Mine Haulage and Truck Shop Operations.* Paper presented at the Australian Mining Technology Conference, Perth.

[7] Kolonja, B., & Mutmansky, J. M. (1994). Analysis of truck dispatching strategies for surface mining operations using SIMAN. *Transactions - Society for Mining Metallurgy And Exploration Incorporated, 296*, 1845-1851.

[8] Leica Geosystems Mining. *Joptimizer*.

[9] Modular Mining Systems Inc. *Dispatch*.

[10] Peng, Shiji, Zhang, Daxian, & Xi, Yongfeng. (1988). Computer simulation of a semi-continuous open-pit mine haulage system. *Geotechnical and Geological Engineering, 6*(3), 267.

[11] Raj, M. G., Vardhan, H., & Rao, Y. V. (2009). Production optimization using simulation models in mines: A critical review. *International Journal of Operational Research, 6*(3), 330-359.

[12] Rockwell Automation, Inc. Arena (Version 14.50.00002).

[13] Sturgul, J. R. (2001). Modeling and simulation in mining - Its time has finally arrived. *Simulation, 76*(5), 286-288.

[14] Sturgul, John R., & Eharrison, John. (1987). Simulation models for surface mines. *International Journal of Surface Mining, Reclamation and Environment, 1*(3), 187-189.

[15] The MathWorks, Inc. *Matlab-R2015b*. Natick, Massachusetts, United States.

[16] Upadhyay, S. P., Suglo, R. S., Lin, Z., Sundararajan, S., & Szymanski, J. (2013). Simulation analysis model and equipment selection in continuous surface mining systems. *CIM Journal, 4*(2), 87-94.

[17] Wenco International Mining Systems Ltd. *Wencomine*.

[18] Yuriy, Greg, & Vayenas, Nick. (2008). Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms. *International Journal of Mining, Reclamation and Environment, 22*(1), 70-83.

Truck-Shovel Simulation Reliability Analysis with Embedded Dispatch Optimizer

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Abstract

Simulation has proven to be a powerful tool for assessing the performance of complicated uncertain systems with numerous interconnected parts with time-varying parameters. Simulation is especially useful where optimization methods fail to capture the complexity of real-world dynamic systems. 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 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. The tool includes a thorough implementation of a dispatching logic which mimics real-world dispatching systems in allocating trucks to the neediest shovels on the shortest travel path. Moreover, a new algorithm is developed for truck allocation by MOL and was implemented in the system. Comparing the new algorithm with the common real-world dispatching systems on a case-study provides a 10% improvement in the production of the operation.

1. Introduction

Mining projects, and more specifically surface mines, are capital intensive ventures with high operating costs. Approximately 50% of the operating costs in open pit mines (Alarie & Gamache, 2002) and even 60% in large open pit mines are allocated to haulage and materials handling (Ahangaran, Yasrebi, Wetherelt, & Foster, 2012; Akbari, Osanloo, & Shirazi, 2009; Alarie & Gamache, 2002; Oraee & Goodarzi, 2007). Therefore, optimization of the operational mine plans and the fleet management has a significant impact on operation efficiency.

Our research endeavors are focused on simulation and optimization of mine operational plans and its interaction with the extraction plants. The preliminary research (Tabesh, Azimi, & Askari-nasab, 2012) is geared towards integration of mine discrete event simulation and fleet management system to optimize the mining operation in one framework. The simulation and optimization tools work together towards generating a near-optimal and practical mine fleet management system working in presence of uncertainty. Correct implementation of the fleet management systems' logic in the integrated simulation and optimization framework is key to the success of this research. The dispatching logic integrated into the mine simulation needs to closely mimic the algorithms and logic implemented in today's industrial mine fleet management systems, such as DISPATCH® (Modular Mining Systems, 2016), Wencomine (Wenco Mining Systems, 2013), Jmineops (Leica

Geosystems, 2016), and CAT® MINESTAR™ FLEET (Caterpillar, 2016). As of majority of mines around the world and almost all of the active mines in north America are using DISPATCH® (Modular Mining Systems, 2016) we simulated a mine operation with embedded DISPATCH® in this paper as a benchmark model to verify reliability of MOL dispatching algorithm.

In the following sections, we first briefly go over the previous mining operation simulation studies. Then in the next section, we introduce some of the currently in use mining fleet management systems where subsections are providing mathematical background of the DISPATCH®. In section four, the system to be modeled, objectives to be achieved in this study, key performance indicators (KPIs), and flow diagram of the simulation model are presented followed by modeling approach in section five. Section six introduces an open pit mine as a case study. Before presenting conclusions in section eight, results of the simulation are presented and discussed in section seven.

2. Literature Review

The fleet management system mainly works based on two different setups: 1) fixed truck allocation and 2) flexible truck allocation. Transition of fleet management systems from fixed to flexible truck assignments has been investigated for more than 40 years. The first dispatching system applied in a limestone quarry operation in Germany showed a great improvement in the efficiency of the equipment (Bonates & Lizotte, 1988). Results of that implementation ended up introducing different dispatching packages with different optimization criteria to mining industry.

In fixed truck allocation setup, at the beginning of each shift a group of trucks is locked to each transportation route. The trucks allocated to the paths are to work on the same path over the shift based on several criteria, such as production requirement, availability of the trucks in the fleet, etc (Y. Lizotte, Bonates, & Leclerc, 1987; Yves Lizotte & Bonates, 1987). The paths to which trucks have been allocated will not change until a shovel breaks down or a critical event happens. Some efforts to modify this method have been seen in the literature. In flexible truck allocation, a number of available trucks in the fleet are assigned to a specific working shovel at the beginning of the shift. But these trucks, instead of being in the service of a single shovel or a single route during the shift, will receive a new assignment from the dispatch system every time after loading at the shovels and tipping at the dumping destinations. It has been shown that flexible truck allocation improves productivity of the operation by a high percentage.

First, Bogert (1964) suggested the use of radio communication between equipment operators and the mine control centre. In the late 1970s, Mueller (1977) introduced implementation of the dispatching boards installed in the control centre. This method of operation scheduling is the least productive method and from Kolonja and Mutmansky (1993) to Hashemi and Sattarvand (2015), it has been consistently used as a base method to study the performance of other algorithms and approaches. Kolonja and Mutmansky (1993) documented differences in production comparing fixed truck allocation and flexible truck allocation strategies. Furthermore, Hashemi and Sattarvand (2015) in a simulation study of the Sungun Copper mine operation showed that by implementing a flexible allocation strategy the productivity of the mine increased by 8% in comparison with the fixed allocation. Olson et al. (1993) reported a 13% increase in the production of the Bougainville Copper Mine using the flexible truck allocation. Also, a 10 to 15% improvement in the productivity of the Barrick Goldstrike Gold mine, a 10% growth in iron ore production at the LTV steel mining, and a 10% increase in the production of the Quintette Coal mine were reported by Olson et al. (1993). Therefore, we will review the literature on flexible truck allocation for the rest of this section.

In Bonates and Lizotte (1988) the authors evaluated application of a dispatching system using a computer simulation model. In the model, fleet management systems were categorized in 3 main groups including: Manual Dispatching, Semi-Automated Dispatching and Automated Dispatching.

The resulted model which was developed in FORTRAN, attempts to take into account the real features of the mine and optimize the utilization of the trucks and shovels as a Linear Programming (LP) objective function. Li (1990) introduced a methodology for optimum control of shovel and truck operation by defining an LP optimization model.

Soumis, Ethier, and Elbrond (1989) developed a nonlinear procedure to solve the mining truck dispatching problems. The algorithm proposed by them, was based on a nonlinear objective function with 3 main components including: deviation of shovels' operational excavation from the objective rate, deviation of trucks' real working hours from their scheduled operating hours, and penalties assigned to deviation from desired quality of input to the plant (Soumis, et al., 1989). Forsman, Rönnkvist, and Vagenas (1993) developed a computer simulation model for Aitik open pit mine operation. In their simulation model graphical model of the mine was built implementing a discrete event modeling microcomputer called METAFORA. Optimum number of trucks required to achieve the production target is obtained from the simulation (Forsman, et al., 1993). Gove and Morgan (1994) worked on truck-shovel matching and the influential parameters using CAT's fleet production and cost (FPC) software (Gove & Morgan, 1994). Ataeepour and Baafi (1999) worked on a simulation model for truck-shovel operation using Arena (Rockwell Automation, 2016) to assess both dispatching and non-dispatching mining operations. Their study can be divided into two major sections: The first step is to monitor the effect of number of trucks in system utilization, and the second step is to develop a dispatching rule based on minimizing truck waiting times. In the same year Basu (1999) proposed a dispatching strategy on the same logic base as developed by Ataeepour and Baafi (1999).

At the beginning of the 21st century, Alarie and Gamache (2002) conducted a research on solution strategies used in truck dispatching systems for open pit mines. Based on their research, dispatching problem can be solved using two major approaches: single stage and multistage. The algorithms developed in a single stage approach send trucks to the needy shovels by solving one order of optimization problem while in a multistage approach an optimum production target is set for the operation using LP or heuristic methods. In the lower stages the assignments are handled in a way that the deviation of operational excavation from the targets, suggested by upper stage, are minimized. Wang, Zhang, Chen, and Xu (2006) studied truck real-time dispatching from a macroscopic point of view. They first defined internal nodes on each path and then evaluated the flow rates of the trucks on each route. Results illustrated that the proposed model shows better results in comparison with the conventional dynamic programming (DP) methods. Burt and Caccetta (2007) proposed another approach for the calculation of a match factor for heterogeneous fleets. Based on their method, if different cycle times are calculated for different truck types and shovel types, a match factor for the fleet is achievable. The proposed method is also capable of considering different haul road features. Krause and Musingwini (2007) used a machine repair analogy to analyze and determine truck fleet size for an open pit mine. They chose Arena (Rockwell Automation, 2016) for the simulation part "because it can be programmed with any number of probability distribution fitted to an unlimited number of cycle variables and is therefore a very flexible model for use in analyzing several variables in shovel-truck analysis".

Jaoua, Riopel, and Gamache (2009) developed a framework for realistic microscopic modeling of surface mining transportation systems. Advantages of the framework were highlighted as a library for the real-time allocation, an updater for the truck allocation, and a fuel controller.

He et al. (2010) implement a genetic algorithm to optimize truck dispatching problems in open pit mines. They tried to find a route and assign an upcoming truck to it based on minimized transportation and maintenance costs. In their model, it has been assumed that truck velocity in both loaded and empty conditions are the same, which is a drawback of their model. Although their major focus was on minimizing the costs, by assuming the same velocity for both loaded and unloaded trucks, they underestimated costs. Another major drawback, similar to almost all other models, is the assignment of trucks to routes rather than to shovel-destinations. Furthermore, they assumed that truck maintenance costs become higher with the age of the truck by a constant coefficient, whereas Topal and Ramazan (2012) showed that maintenance cost behaves in a fluctuated manner during its life and it will decrease considerably after every overhaul.

Another model provided by Subtil et al. (2011) is used in the commercial package SmartMine® marketed by Devex SA (Devex, 2016). It uses LP, in the upper stage, to determine the maximum production capacity of the mine and the optimal size of the truck fleet required to meet the target production. The allocation planning stage completely remains to the planner. Moreover, the model does not take into consideration other desired characteristics such as grade blending and constant desired feed to plants. The dynamic allocation or the truck dispatching is achieved by adopting *M* trucks for *N* shovels strategy. Using M trucks, the best possible solutions based on undisclosed criteria are generated and each solution is simulated 50 times to achieve a desired confidence interval. The best solution is found using a multi-criteria optimization, which maximizes productivity of the transport fleet and minimizes queue time at shovels and idle time of shovels. A fuzzy logic expert system is then used to evaluate the solution and, if passed, dispatch the truck to the allocated shovel. The major drawback of the approach can be the cumbersome time consuming methodology adopted at the dynamic allocation stage, which requires real- time decisions. The authors of this study mention situations where fuzzy logic rejects the best solution and requires re-running of the entire model to obtain another solution. The alternate solution generated after rejecting the first one will be the second best solution, which may again get rejected, leading the method in a time-consuming loop.

Ahangaran et al. (2012) use a two stage model for truck dispatching, where the first stage uses a network analysis technique to determine the best routes between departure and destination points and second stage provides dynamic truck assignments. The second stage adopts a binary integer programming model to minimize the function of the total cost of loading and transportation. This dispatching model is significantly different compared to previous models in terms of the objective function and the mixed fleet considerations in the modeling equations. One of the major drawbacks of this model is that it does not consider traffic over the routes during the procedure to find the shortest path. Another drawback is that, although their objective function is to minimize total truck cycle time, they do not take into account truck spot time and truck waiting time at both shovels and crusher. They did not show the practicality of their model in at least one open-pit mine. As one of the latest studies in the field of open pit mining operation simulation, Que, Anani, and Awuah-Offei (2016) investigated the effects of implementing real-time correlated variables as non-correlated single input distribution on the final results of the simulation modeling. The results show the correlation exist in truck-shovel operations, although it depends on sensitivity of the results to the input variables as well as strength of the correlation.

3. Fleet Management Systems

There are many companies across the world providing mine fleet management systems. Some of the more popular ones are as follows: Modular Mining Systems, which is used in over 200 mines around the world (Modular Mining Systems, 2016), Jigsaw Software, which is installed in 130 mines (Leica Geosystems, 2016), and Wenco, which currently has 65 mine sites across the world (Wenco Mining Systems, 2013). TATA consultancy services has introduced Dynamine with a range of productivity improvement of 10% to 15% (TATA consultancy services, 2016). However, Micromine with Pitram system (Micromine, 2009) and Caterpillar with CAT® MINESTAR™ FLEET (Caterpillar, 2016) are the next leaders of mine fleet management systems.

The algorithms behind commercial mine fleet management systems are proprietary information, and therefore the companies do not disclose the logics. Consequently, a comparison of the optimality of the fleet management solutions is not feasible. However, in the 1980s and early 1990s, the Modular Mining System (Olson, et al., 1993; White & Olson, 1986) published their models and algorithms, and based on these, the DISPATCH® (Modular Mining Systems, 2016) mine fleet management system has been developed. Thus, in this section we review the algorithms behind DISPATCH® (Modular Mining Systems, 2016) that were publically available.

Figure 1 and Figure 2 illustrate the procedure DISPATCH® (Modular Mining Systems, 2016) follows to find the solution and the algorithms implemented to complete the tasks, respectively. First, the data from the pit and manual assignment are input to DISPATCH® using forms. Then, the shortest paths to send material from loaders to the destinations are found using the Dijkstra algorithm. As the next step, an LP model is run to find the optimum material flow rate of each route. Finally, using DP, trucks in the available trucks list are assigned and all information is updated.

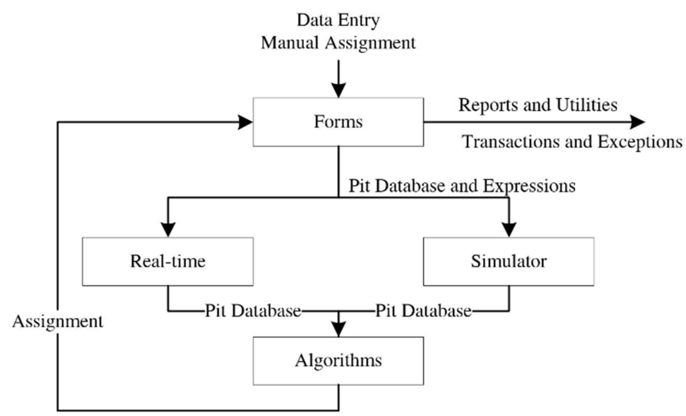

Figure 1: Schematic representation of DISPATCH® block diagram

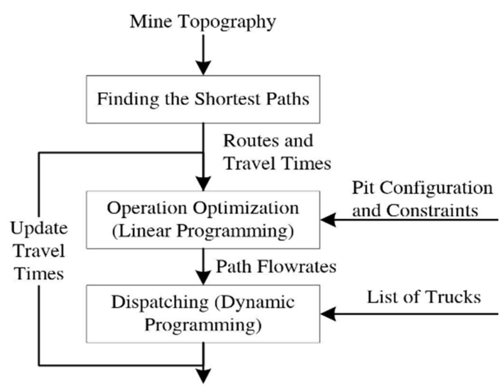

Figure 2: Procedure through with DISPATCH® assigns trucks

4. DISPATCH®

4.1. Finding the shortest path - DISPATCH®

In graph theory, the shortest path problem is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimized. To find the shortest path, DISPATCH® uses Dijkstra's algorithm with the objective of minimizing travel time between each pair of starting and ending points. After solving the shortest path problem in DISPATCH®, the following information is presented to the operation optimization model: 1) total minimum distance and travel time for each specific transport and 2) the nodes trucks must pass through to reach the destination.

4.2. Production optimization - DISPATCH®

DISPATCH® uses linear programming approach to optimize the production target within a specific time horizon by dividing it into two separate but weakly coupled models. The first one, Eq. (1), optimizes the total production of the operation, including mining, processing, and stockpiling, and the second part, Eq. (5), maximizes the fleet production by minimizing the total required volume to be handled. The second part generates a theoretical haulage master plan that considers production and operational constraints and is later used as a reference to generate real-time truck assignments. White and Olson (1986) and Olson et al. (1993) describe the model as follows:

$$\min C = \sum_{i=1}^{N_m}(C_m \times Q_i) + C_p \times (P_t - \sum_{i=1}^{N_m+N_s} Q_i) + \sum_{i=1}^{N_s}(C_s \times Q_i) + \sum_{i=1}^{N_m+N_s}\sum_{j=1}^{N_q}(L_j \times C_q \times X_{ij} \times Q_i) \tag{1}$$

Subject to:

$$0 \le Q_i \le R_i \tag{2}$$

$$P_t \ge \sum_{i=1}^{N_m+N_s} Q_i \tag{3}$$

$$X_j L \le X_j A + \sum_{i=1}^{N_m+N_s}\left(X_{ij} - X_j A\right) \times Q_i \times T_c / \left(M_c / SG\right) \le X_j U \tag{4}$$

Where:

N_m, N_s, and N_q	are the number of shovels at mining faces, the number of shovels working at stockpile, and the number of quality constraints
C_m, C_s, C_q, and C_p	are the material transportation pseudo cost (hr/m^3), the stockpile material handling pseudo cost (hr/m^3), the quality pseudo cost (hr/m^3), and the pseudo cost of low feed to plant (hr/m^3)
Q_i	is the material being transported per hour (m^3/hr) that should be determined in the procedure
L_j	is the quality director: 1 for low crit and -1 for high crit
X_{ij}, $X_j L$, $X_j A$, and $X_j U$	are the j^{th} quality factor at i^{th} shovel, the lower limit for quality factor *j,* the running average value of quality factor *j,* and the upper limit for quality factor *j*
P_t	is the target rate of plant feed
R_i	is the digging rate at i^{th} shovel
M_c	is the 1st in/1st out average control mass, kg
SG	is the specific gravity
T_c	is the base control interval (hr)

All pseudo costs are chosen arbitrarily with respect to ($C_m < C_q < C_s < C_p$).

As the second segment of the LP model, DISPATCH® tries to minimize total haulage capacity needed to meet shovel production coverage:

$$\min V = \sum_{i=1}^{N_p}\left(P_i \times T_i\right) + \sum_{j=1}^{N_d}\left(P_j \times D_j\right) + N_e \times T_s \tag{5}$$

Subject to:

$$\sum_{k=1}^{N_{pi}} P_k = \sum_{k=1}^{N_{po}} P_{k'} \tag{6}$$

$$R_j = \sum_{k=1}^{N_{po}} P_{k'} \quad \text{for mining shovels} \tag{7}$$

$$R_j \le \sum_{k=1}^{N_{po}} P_{k'} \quad \text{for stockpiles} \tag{8}$$

$$P_j = Q_i \tag{9}$$

$$0 \le P_i \tag{10}$$

Where:

V is the total mine haulage (m^3)
N_p is the number of feasible haul routes
P_i is the haulage on path *i* which should be determined (m^3/hr)
T_i is the path *i* travel time (hr)
N_d is the number of dumps for mine haulage
P_j is the net haulage input to dump *j* (m^3/hr)
D_j is the average dump time at dump *j* (hr)
N_e is the number of operating shovels
T_s is the fleet average truck size (m^3)
N_{pi} is the number of feasible input paths at node *j*
N_{po} is the number of feasible output paths at node *j*
P_k is the input path haulage (m^3/hr)
$P_{k'}$ is the output path haulage (m^3/hr)
R_j is the limiting rate at node *j* (m^3/hr)

The model, Eq. (1), introduces the first segment of the operation optimization as a pseudo cost-based LP, which is established on the summation of costs in all four operational sectors of the mine. The solution of the first segment presents the shovels' production rates with respect to the maximum digging rate for a shovel, Eq. (2), the maximum capacity of the plant, Eq. (3), and the lower and upper bounds of the blending grade, Eq. (4). The second segment's LP maximizes the production of the operation by allocating a minimum number of trucks to each active route, Eq. (5) to meet the routes production rate. Eq. (6) makes sure that the input and output flow at each shovel and each dumping point are equal. Eq. (7) and (8) guarantee that the amount of material handled meets the grade requirements at the plant cannot exceed the amount produced by the mine and stockpile. Coupling segments of the operation plan is attained by constraining total production of all routes servicing a shovel to be greater or equal to the shovel production, Eq. (9). It should be mentioned here that both P and Q in Eq. (9) are vectors. Finally, Eq. (10) ensures that all haul rates in the mine are nonnegative. One benefit of the model is that it follows the current status of the mine by using real-time data. Another advantage of the model is that the optimum production rate of each route is based on the volume of material, not based on the number of trucks. That helps the dispatching step to send the proper truck to cover the shortage. A major drawback of the model is that it does not consider stripping ratio limitation in the operation. By limiting the lower bound of digging rates at each shovel to zero, they allowed the model to ignore a shovel operating at waste mining face. Another disadvantage of the model is that the plant head-grade requirement is constrained to a range of grade between predefined upper and lower limits. It will cause an undeniable short-term influence on both plant output (final product) quantity and its input (utilization of some specific shovels which must be met up to the minute) (Temeng, Otuonye, & Frendewey, 1998). However, most of the drawbacks of DISPATCH® will arise in the real-time dispatching model that will be explained in more detail in the next section.

4.3. Real-time Dispatching - DISPATCH®

After solving the upper stage – operation optimization – LP problem by implementing the Simplex method (Dantzig, 1951), resulting in the optimum material flow rate on routes, White and Olson (1986) employ the dynamic programming (DP) (Bellman, 1954) approach to send trucks to the proper destination. To do so, two lists and three parameters are defined. A list of needy shovels or LP-selected paths and a list of trucks dumping material at discharge points or en-route from a loading point to a destination are provided. In addition, need-time, Eq.(11), which is defined as the expected time for each path's next truck requirement, is formulated as follows:

$$need-time_i = L_j + F_{ij} \times \left(A_j - R_j\right) / P_i \tag{11}$$

Where:

L_j is the time the last truck was allocated to the shovel *j*

F_{ij} is flow rate of path *i* over the total flow rate into shovel *j*

A_j is total haulage allocated by time L_j to shovel *j*

R_j is haulage requirement of shovel *j*

P_i is path flow rate (ton/hr or m^3/hr)

So, the neediest path, which is on the top of the neediest shovels list, will be the one with the shortest need-time. Then lost-ton is defined and formulated as a criterion to find the best truck for the neediest path from the truck list with Eq.(12):

$$lost-ton = \frac{truck\,size \times total\,rate}{required\,trucks} \times \left(truck\,idle + excess\,travel\right) + shovel\,rate \times shovel\,idle \tag{12}$$

Where:

Truck size is the size of truck being assigned; Total rate is total digging rate of all shovels in the mine; Required trucks is total required trucks in the LP solution; Truck idle is expected truck idle time for this assignment; Excess travel is extra empty travel time to neediest shovel; Shovel rate is sum of all path rates into neediest shovel; And shovel idle is expected shovel idle time for this assignment.

Considering the lost-ton definition, the truck covering lost-ton of neediest shovel the most is the best truck. After the best truck is assigned to the neediest shovel, it is moved to the last position on the needy paths' list and the procedure is repeated for the second neediest until all trucks on the list are assigned.

Defining a rolling time horizon when a sequence of assignment is needed is a benefit of the model. The information of the mine status used in the model is always up to the minute. However, the model does not consider the effect of current truck assignment on the forthcoming truck matching, though all trucks previously sent to the shovels are considered. Another drawback of the model is that despite the authors' claim, the solution method is not a DP. It is a heuristic rule solving each sub-problem based on the best solution of previous sub problems. According to Alarie and Gamache (2002), the solution method's misnaming as a DP is perhaps because of the authors' misunderstanding of Bellman's principal of optimality. However, the DISPATCH® system has been implemented in about 200 mines all around the world (Modular Mining Systems, 2016). Table 1 summarizes the procedure with which DISPATCH® solves a mine production problem.

Table 1: Summary of the models DISPATCH® uses in the fleet management systems

Category	Shortest Path	Allocation	Dispatch
Objective	Minimize travel time	Minimize total trucks required	Minimize lost-tons caused by the assignment
Constraints	Intermediate call points a truck should pass	Shovels' digging rate Dump area capacity Continuity at each loading and discharge point Total number of trucks available in the fleet Blending limits of grades Targets of material category blending	Proximity of truck that asks for an assignment to the destination
Solution Method	Dijkstra	Simplex	Dynamic Programming
Advantages	Algorithm often does not have to investigate all edges Dijkstra's algorithm has an order of n^2 so it is efficient enough to use for relatively large problems	Model is up to the minute Flowrate of each route is based on the volume of the material rather than number of trucks	Progressing time horizon when order of assignment is required Under-/Over-truck conditions considered
Disadvantages	Model is time consuming Failure in cases of negative edges Global information of the road network required	Appropriate when a few variables are at play Non-negative constraints for all variables	Definition of a progressing time horizon for an order of assignment Consideration of under-/over-truck conditions

5. MOL heuristic

The algorithm follows 1-truck-n-shovel approach addressed by Alarie and Gamache (2002). In this approach, the shovel 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.

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.

6. System Definition

6.1. System

In this paper, a whole mining operation is studied. The system includes one open-pit mine, haul network, 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 DISPATCH 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. In the system with MOL heuristic, simulation model runs the MOL algorithm instead of DISPATCH when a truck dumps its load. Another major optimization component of the system is the linear programming segment of DISPATCH that runs every 30 minutes and whenever the system experiences a major change. Figure 3 illustrates the flow diagram of the operation.

6.2. Objective of the simulation

The main goal here is to analyze and verify the reliability of the MOL dispatching algorithm with respect to DISPATCH® in simulation modeling of mining operation. To achieve this goal, we use the Gol-E-Gohar open pit mining system as a case study.

6.3. Key Performance Indicators

We have to define major Key Performance Indicators (KPIs) in order to compare the two systems and asses the reliability of our algorithm. Here in this specific project 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.

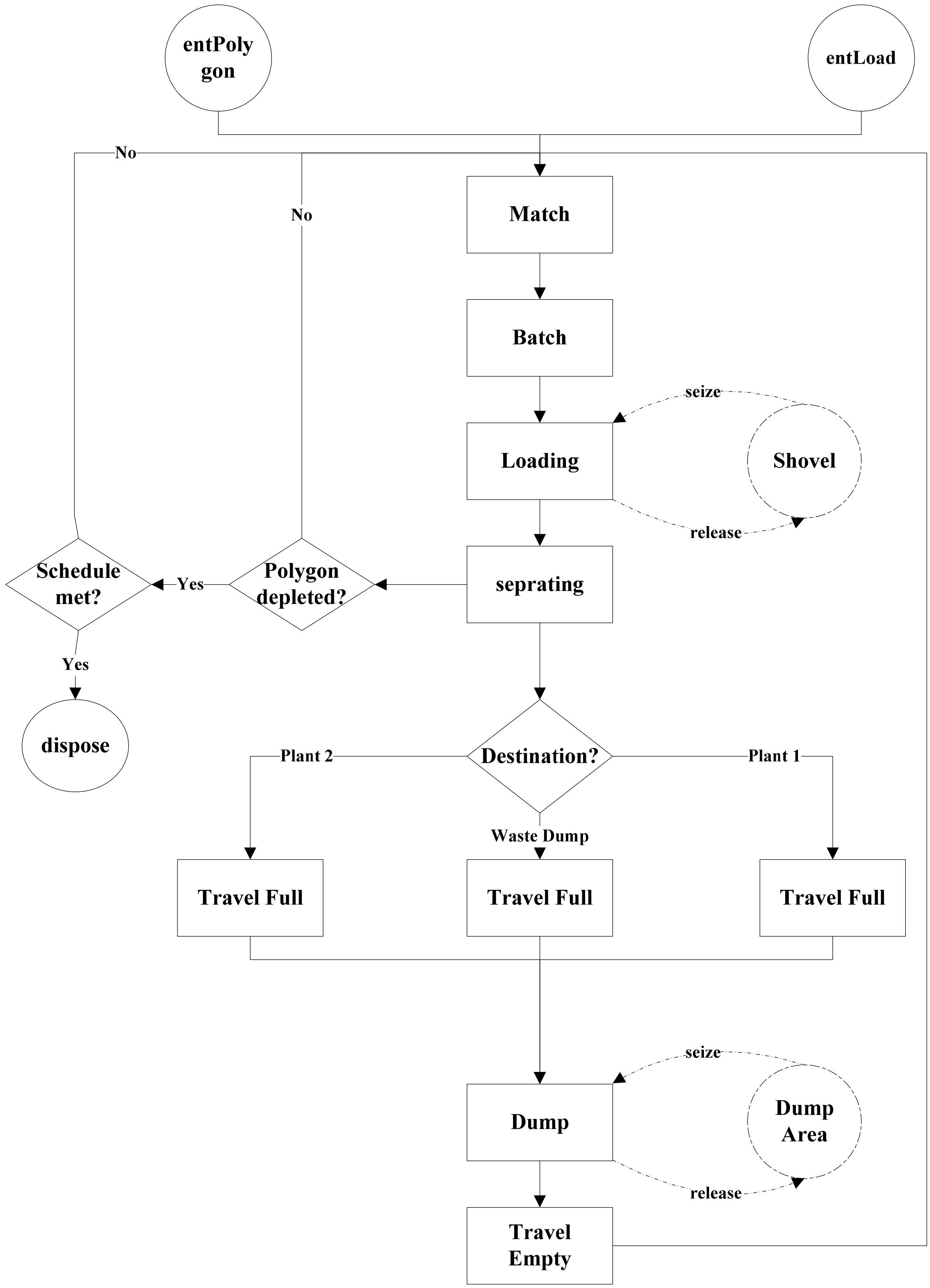

Figure 3: Flow Diagram of the Mining Operation Simulation Model

7. Case Study – Gol-E-Gohar Iron Ore Mine

7.1. 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 (Figure 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). Figure 5 shows the location of loading and dumping points as well as the road network for the year 11 of the operation. Furthermore, Table 2 presents general specifications of the operating system. It is also worthnoting that the mine operates for a single 12-hour shift a day for 340 days a year.

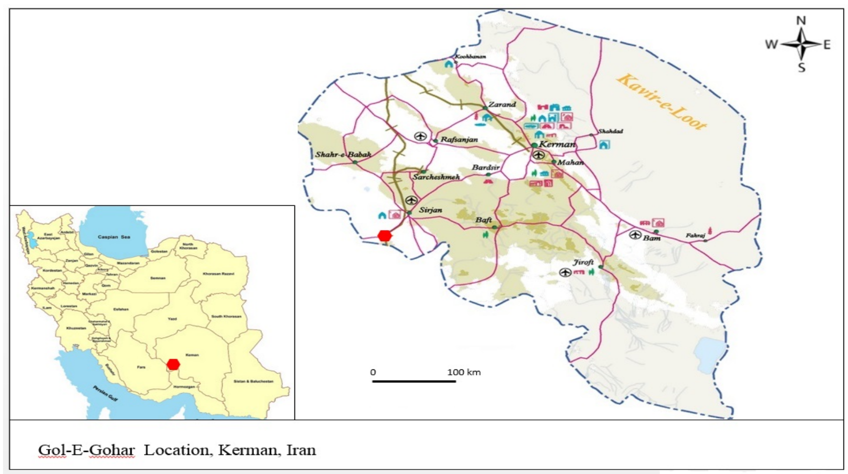

Figure 4: Location of the Gol-E-Gohar Project in Kerman Province of Iran

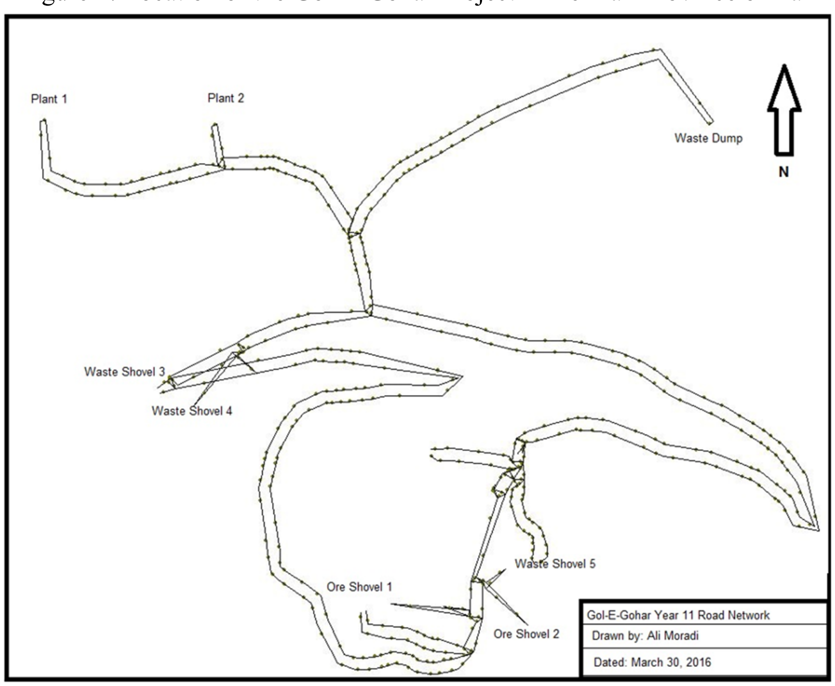

Figure 5: Gol-E-Gohar Iron Ore Mine Year 11 Road Network and loading and dumping locations

Table 2: General specifications of the operation fleet

No.	Loading Point	Destination	Starting Distance (m)	Loader	Hauler
1	Shovel 1	Plant 1	4129	Hitachi EX2500	Cat 785C & Cat 793C
		Plant 2	3626		
2	Shovel 2	Plant 1	4196	Hitachi EX2500	Cat 785C & Cat 793C
		Plant 2	3693		
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

7.2. Input parameters into the simulation model

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. Using Kolmogorov-Smirnov and Chi Square tests, the best function with the least square error from the empirical data was selected for each parameter. Figure 6 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 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 3 introduces the best fitted models on some of the aforementioned parameters to be used in the simulation.

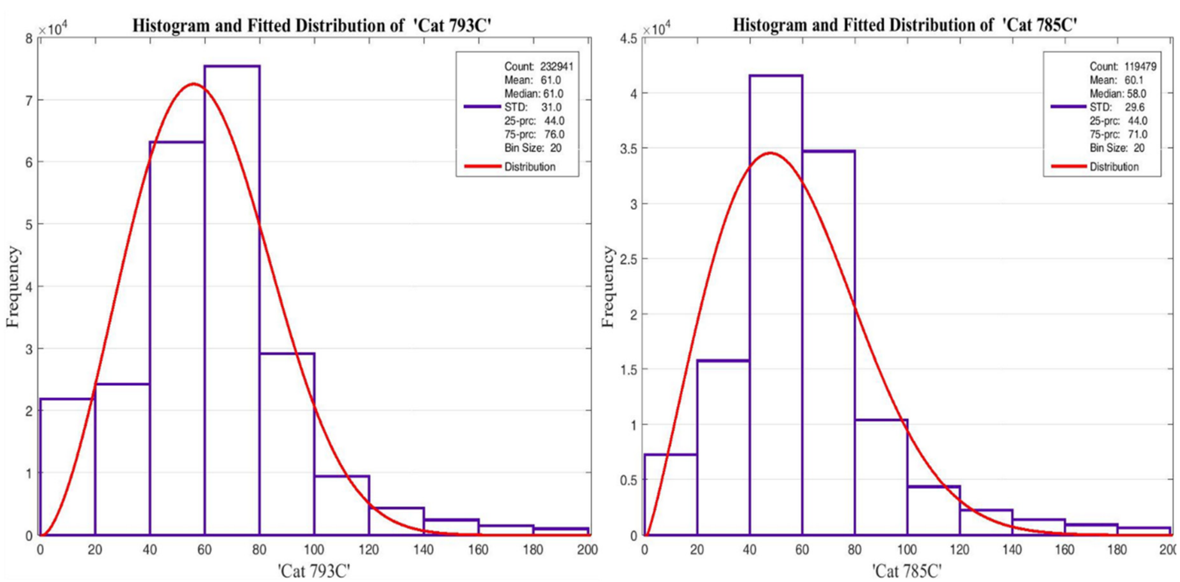

Figure 6: Best fitted distributions on dump time to be used as input parameter in simulation: a) time (seconds) it takes Cat 785C to dump its loaded material; b) Cat 793C dump time (seconds)

Table 3: 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)

8. Results

In this paper, we have built two simulation models to investigate the DISPATCH optimization algorithms (i.e. upper stage LP algorithm and lower stage DP algorithm) and compare it against a heuristic algorithm developed in MOL based on some modifications on DISPATCH. We have used historical mining data to create random distributions for various input parameters and built the models in Arena simulation package. The two models and the verification process are explained in the following sections.

8.1. Input parameters' distribution

As the first section of the reliability analysis, we look at the random distribution functions fitted on historical data and compare them against the historical. We ran the simulation model with the fitted distributions and compared the sampled values against historical values by plotting histograms of the two sets of data, a quantile-quantile plot and a box-plot of the simulated values. As examples, we present empty velocity of Cat 793C trucks, loaded velocity of Cat 793C trucks, backing time of the same truck types, loader bucket tonnage when a Hitachi EX2500 shovel loads a Cat 785C truck, time it takes Cat 793C trucks to dump their load into a dumping point, loading cycle time for Hitachi EX2500 loading Cat 785C trucks, and spotting time when a Hitachi EX2500 loads a Cat 793C are illustrated in Figure 7 to Figure 13, respectively. Looking at these figures we can conclude that the random distributions fitted on historical data are verified to a good extent and we can move forward to running the models and obtaining simulation results for the two models.

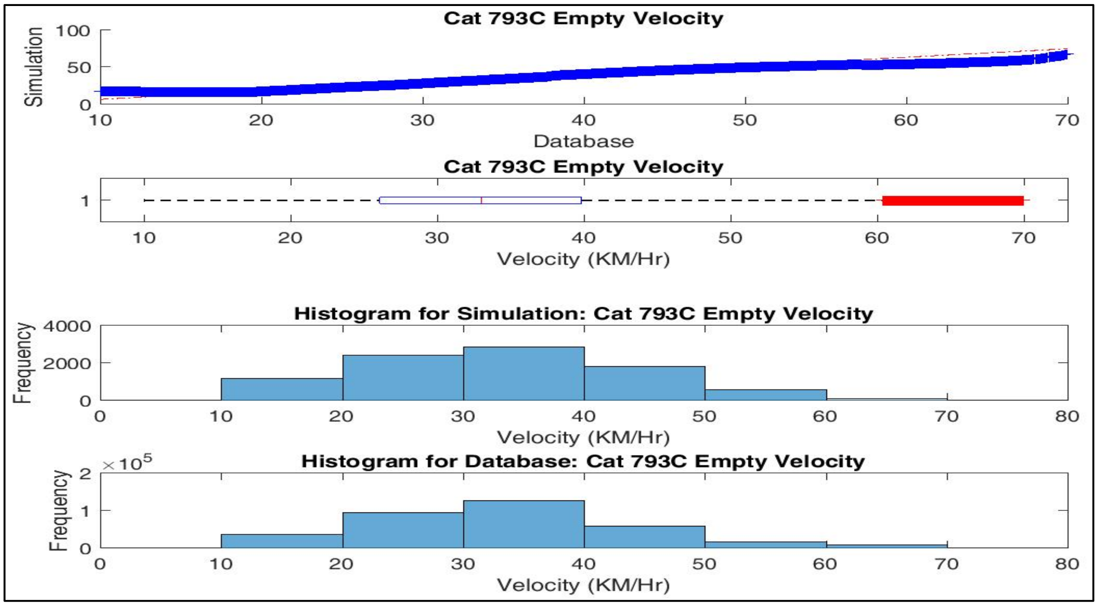

Figure 7: Truck type Cat 793C empty velocity: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

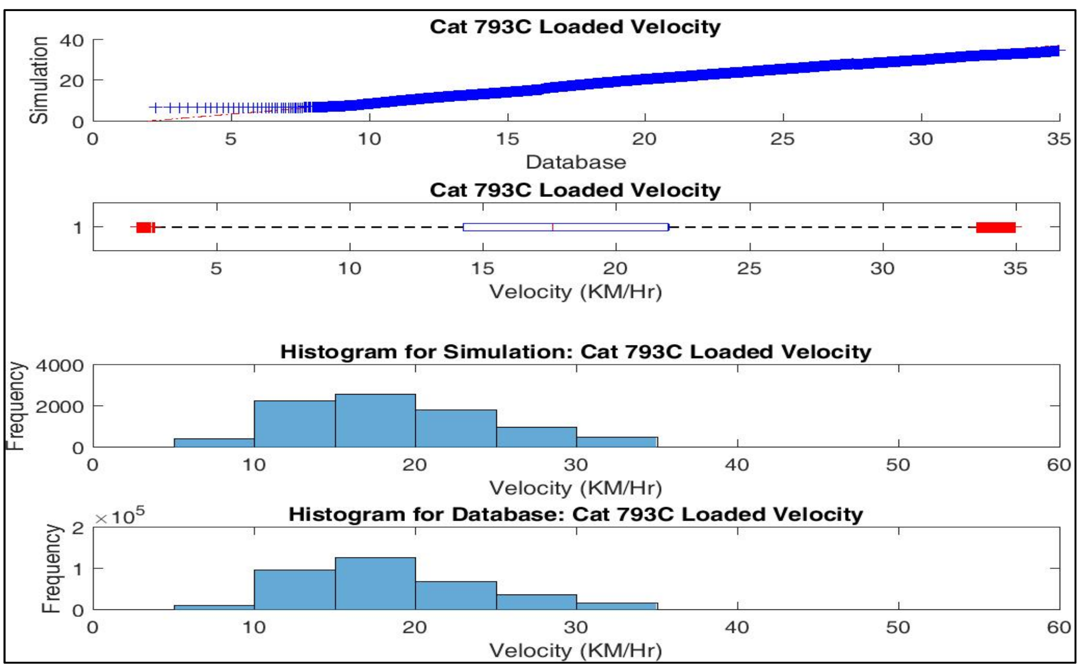

Figure 8: Truck type Cat 793C loaded velocity: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

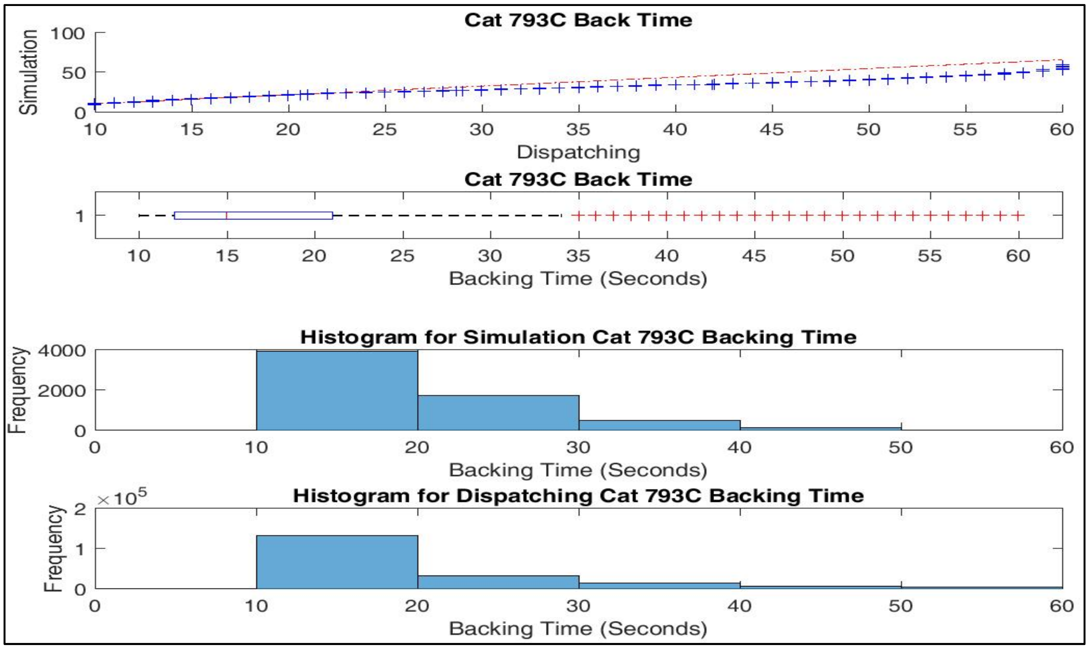

Figure 9: Truck type Cat 793C backing time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

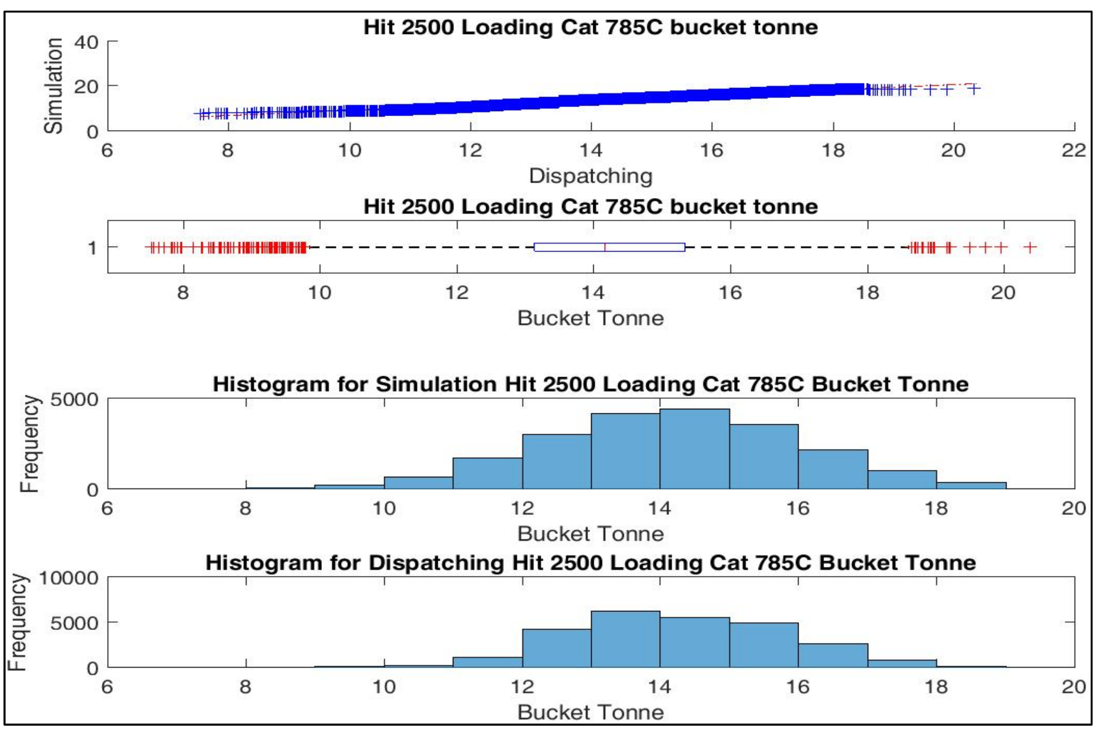

Figure 10: Shovel type Hitachi EX2500 loads truck type Cat 785C bucket tonnage: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

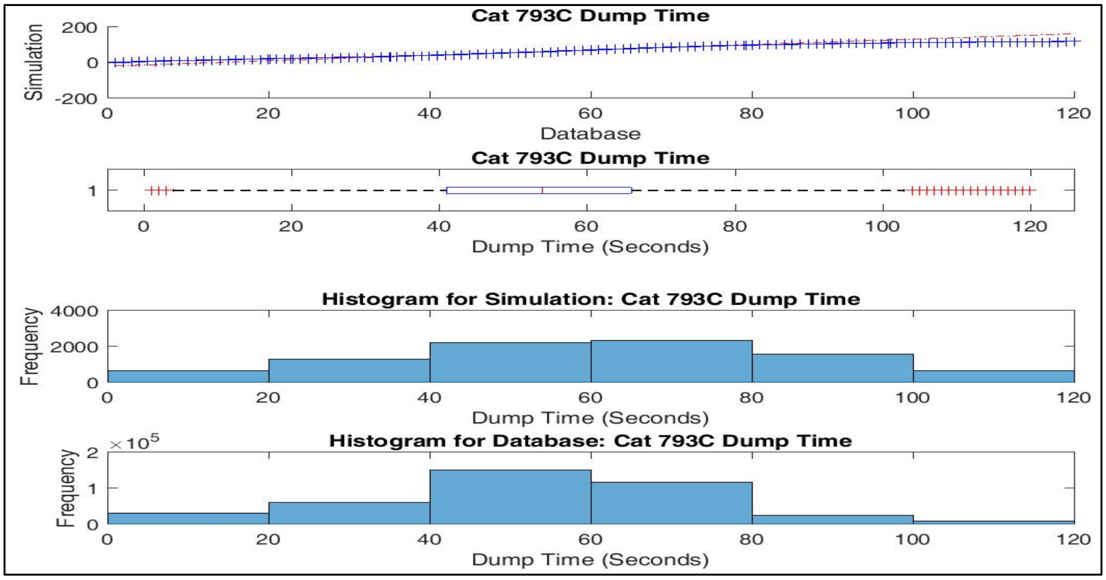

Figure 11: Truck type Cat 793C dump time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

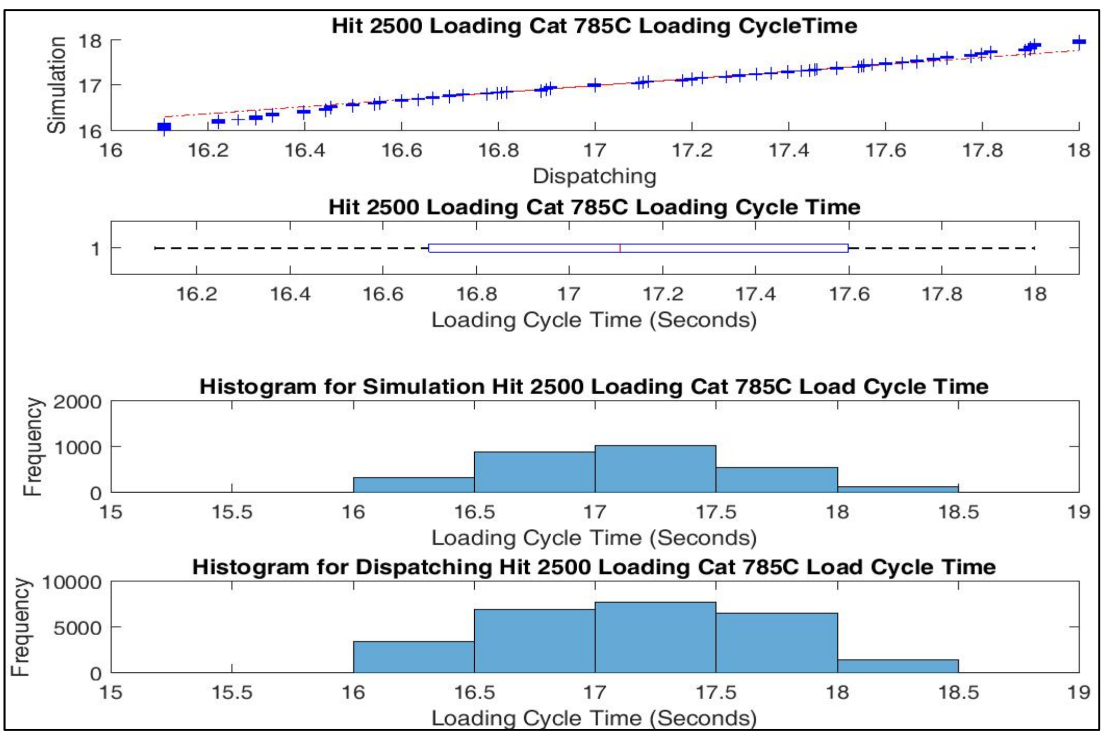

Figure 12: Hitachi EX2500 loading Cat 785C loading cycle time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

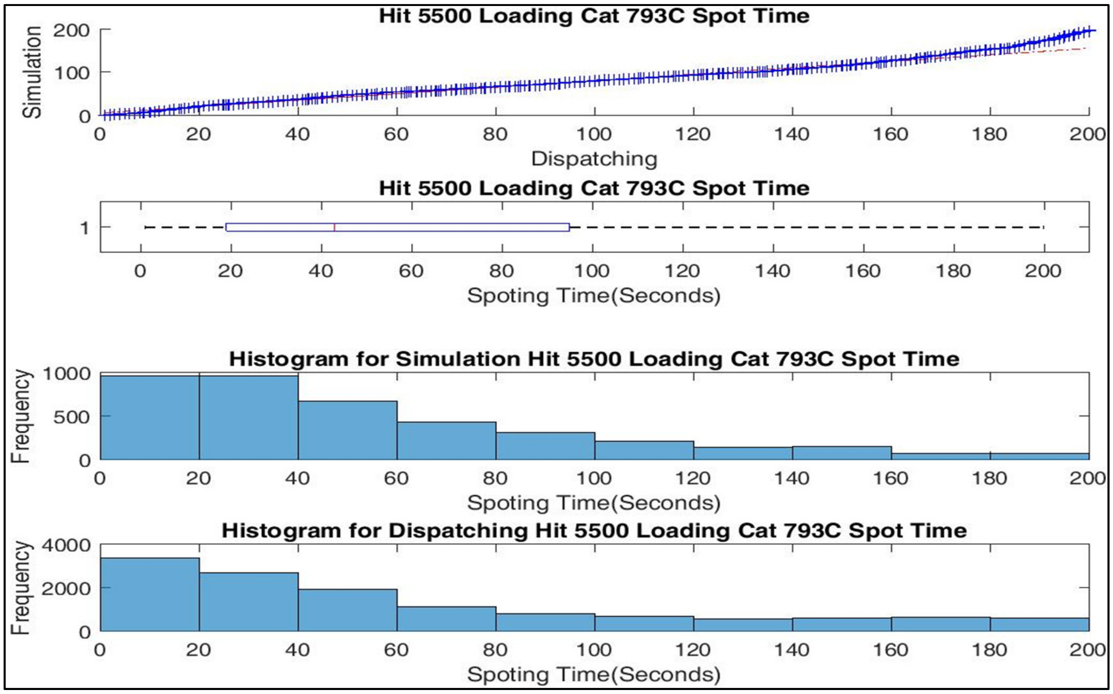

Figure 13: Hitachi EX5500 loading Cat 793C spotting time: quantile-quantile plot, box plot of the simulated values, and histograms of collected data from the simulation results and database, respectively.

8.2. Production

After proving that the distributions representing the uncertain input parameters match with the database, the simulation model was set up for 5 replications (decided based on required halfwidth shown in Figure 14 and Figure 15). Then, the model was run two times each time for 91 days of operation. At the first step, the model was run with the embedded DISPATCH. Afterwards, MOL dispatching heuristic was used to handle the truck assignments. Finally, the results of the two models were compared. The comparison considering weekly production of ore, removing the waste, and input material into each plant are represented in Figure 14 to Figure 21. Both models work using a short-term production schedule obtaiend from (Upadhyay & Askari-Nasab, 2016).

Results of the Gol-E-Gohar mining operation simulation model show that total weekly production of the mine with embedded DISPATCH starts with 1.08 million tonnes per week in the first week of the study. After having a smooth fluctuation between week five and week eight the production reaches a steady weekly rate of 92.5% of its initial production and 88.4% of the maximum acheivable production of the system (Figure 14). On the other hand, the operation does not feed both of the plants with the same rate. Figure 14 shows that plant 2 is always being fed by 20 to 35% more than plant 1 since it is closer to pit.

The same simulation model for the case study was run with the embedded MOL heuristic to dispatch trucks. The result of the 91 days of the operation is presented in Figure 15. At the first week, the operation starts with removing 1.09 million tonnes of ore and waste meeting its highest production on week five with a 4% increase and its lowest production on week six with 3% short comparing with the first week of the operation. The operation reaches a steady state from week seven. Morover, the processing plants are fed almost balanced with a gap of less than 5% difference between the amounts of material sent to each of the plants.

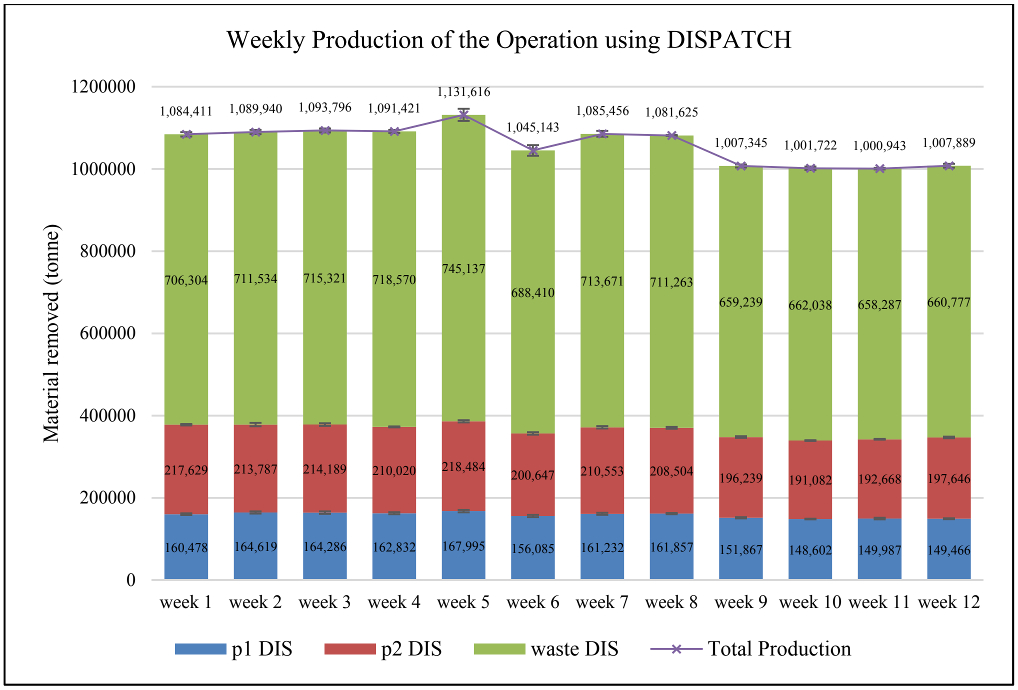

Figure 14: Weekly production of the operation using DISPATCH as the fleet management system over 12 weeks of the operation.

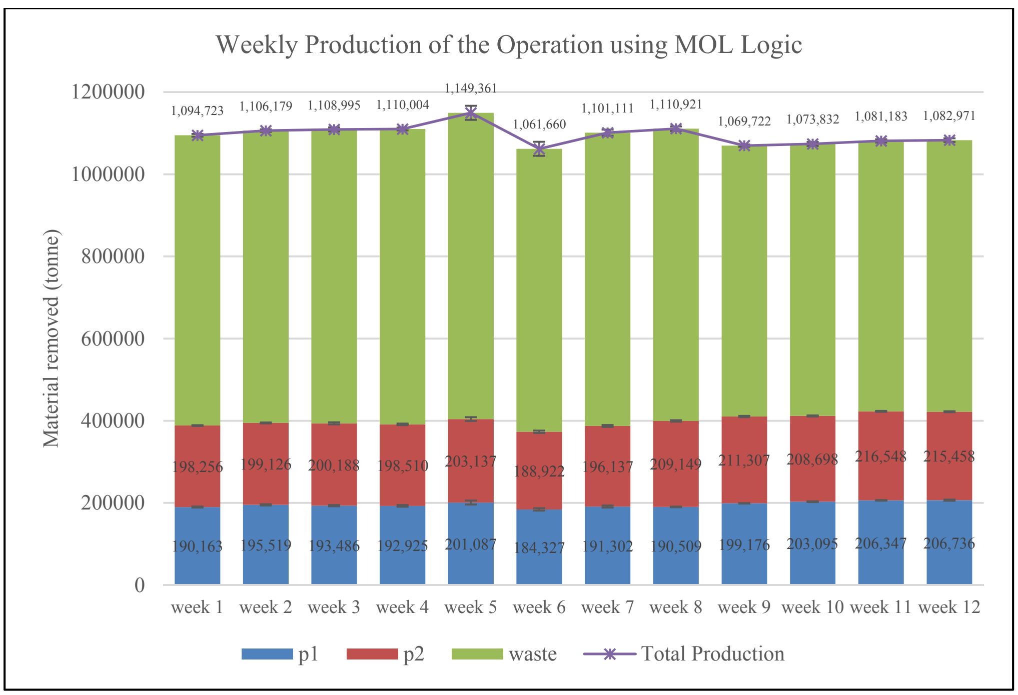

Figure 15: Weekly production of the operation using MOL fleet management system over 12 weeks of the operation.

8.3. Queue at shovels

Number of trucks in queue at each loader is one of the important KPIs to evaluate the performance of a dispatching technique. To have a more representative graph, box plots of queue length at shovels are presented in Figure 16for over the first 20 shifts of the operations. The upper graph illustrates how trucks line up in queue of shovels in the simulation model with embedded MOL heuristic. The second graph in Figure 16 shows the number of trucks in queue at shovels in each shift when the simulation model uses DISPATCH as its fleet management system.

Although the first graph in Figure 16 represents that 35% of the time there are less than or equal to two trucks in line of the shovels when MOL heuristic is being used, investigation over the period of 20 days as shown on the same figure prove that both dispatching systems have almost the same line up in queue of shovels over the shifts.

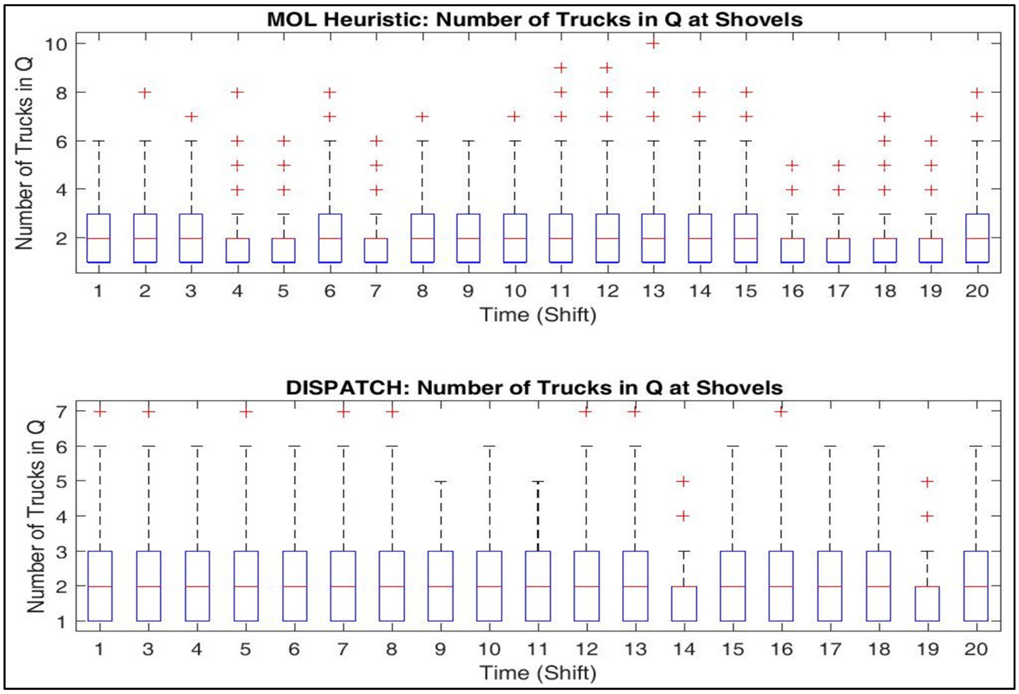

Figure 16: Queue length at shovel 1 per shift: upper plot stands for MOL logic and lower plot presents simulation with embedded DISPATCH

8.4. Shovel utilizations

As one of the most expensive mining equipment in open pit mining operation, utilization of the shovels is one of the important KPIs to measure in the open pit mining simulation modeling. As it was mentioned in the case study section of the paper, there are five active shovels working in Gol-E-Gohar open pit mining operation: three Hitachi EX2500 and two Hitachi EX5500. Utilizations of these five active shovels were tracked over the simulation time of 91 days of the operation. Figure 17 provides overall instantaneous utilization for the shovels. Orange bars stand for shovels' utilization in the operation with embedded DISPATCH and the blue bars represent utilization of the shovels in the operation using MOL heuristic to dispatch trucks to the shovels.

Figure 17 shows that in the operation with embedded DISPATCH send more trucks to shovel 5 than shovel 1. The reason is that DISPATCH is considering minimum distance to send truck to the shovels. Here in this case shovel 5 is working in a closer distance to the dumping points than shovel 1 which is working in the bottom of the pit. As a result, DISPATCH sends more trucks to the shovel 5 than shovel 1. However, in the mining operation with the same priority shovels preference is to produce as much ore material as possible. As shown in Figure 17 the rule is followed by MOL logic. It is sending more trucks to the ore shovel (shovel 1) than the waste shovel (shovel 5) increasing the ore production.

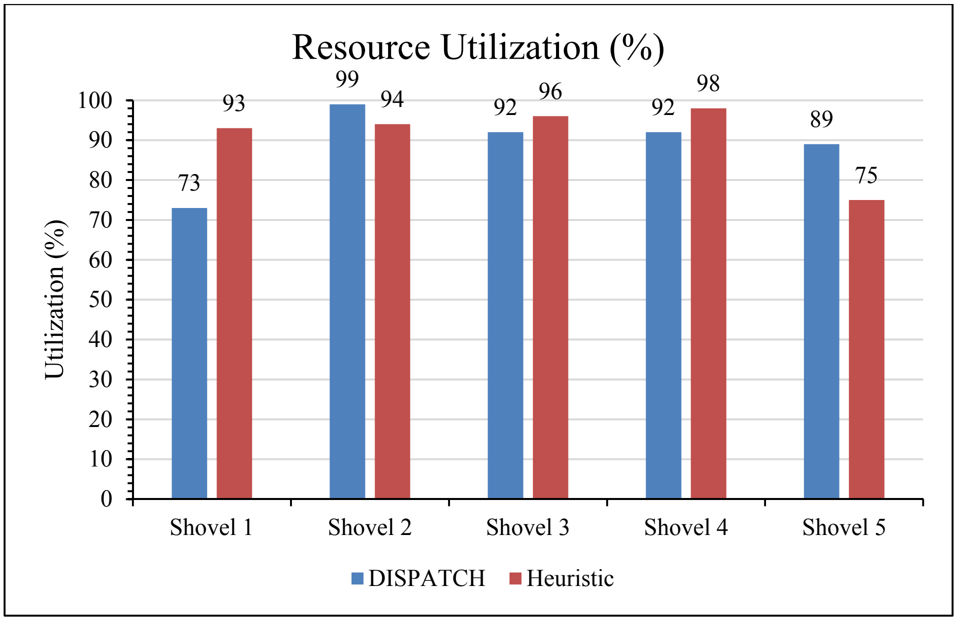

Figure 17: comparing shovels' utilization (MOL logic vs. DISPATCH)

9. Discussions

First of all, as presented in the first section of the results, Figure 7 to Figure 13 illustrate accuracy of the distributions used in the simulation modeling for the six main uncertain input parameters consisting of trucks' speed when they travel empty (Figure 7), loaded velocity of the trucks (Figure 8), time it takes a truck to back up at a dump location (Figure 9), shovels bucket tonnage when loading an specific truck type (Figure 10), dumping time of trucks at dumping points (Figure 11), loading cycle time (Figure 12), and spotting time of the trucks (Figure 13). The quantile-quantile plots of the samples obtained from the simulation results versus the data collected from the database for fitting the random distributions and the histograms of the simulation results and collected data verify that all of the random distributions are fitted properly on the collected data.

After running the simulation for 3 months of the mining operation as the case study, production KPIs of the models were extracted. Figure 18 shows the total amount of material removed from the mine on a weekly base. According to Figure 18 operation implementing MOL heuristic produces higher tonnage of material over the research period except for week one and week five. Results show that in the first week simulation model with embedded DISPATCH produces 0.8% in the first week and 0.2% in the fifth week more than the second model. However, the MOL heuristic helps the operation to remove almost 4% more material over 3 months of the operation. Figure 19 and Figure 20 represent comparison between total ore production as well as weekly feed to each of the active plants, respectively. Considering the average total ore produced over each week of the operation, the model implementing MOL heuristic sends about 9.8% more material to the plants than the benchmark model with embedded DISPATCH (bars in Figure 19 and blue line graphs in Figure 20). Comparison between material sent to each plant (green graphs showing ore sent by MOL heuristic and red graphs showing ore sent by DISPATCH in Figure 20) an average of 30% difference between feeds of plant 1 and plant 2 in DISPATCH is corrected to a gap of less than 5%. The reason behind 30% difference in total plant feeds in DISPATCH is that plant 2 is closer to the pit rim than plant 1. However, this closeness does not have any effect on the material sent to the plant in the model using MOL heuristic. Another aspect of the result of the study to be discussed is that the operation has higher stripping ratio when implementing MOL logic in comparison with the operation using DISPATCH by 5% (Figure 21).

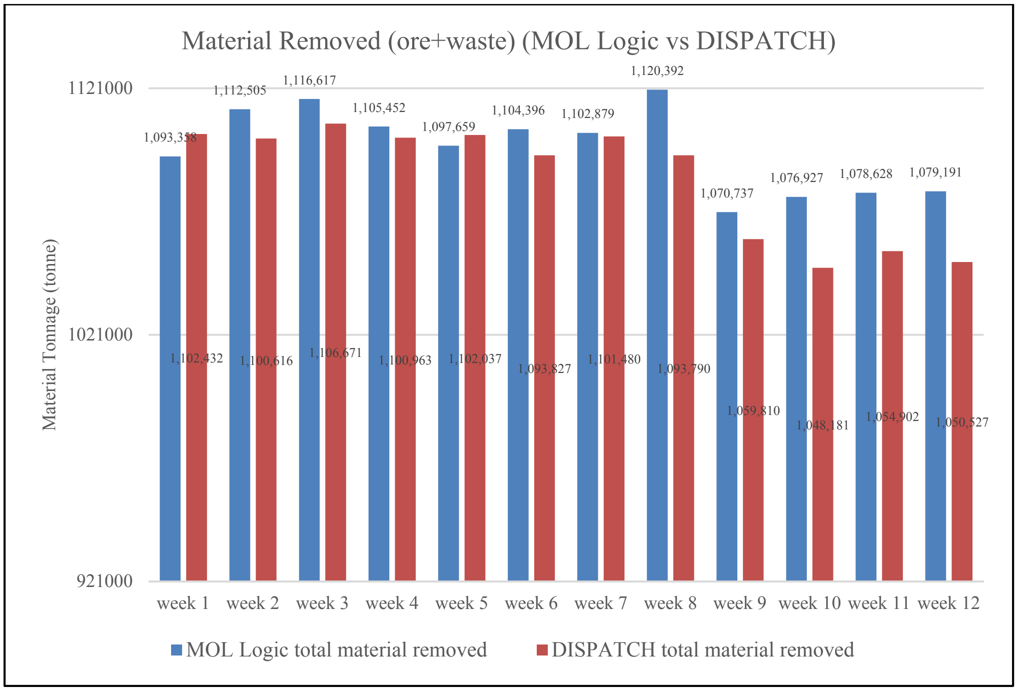

Figure 18: Total material mined including ore and waste over 12 weeks of the operation (a comparison of MOL with DISPATCH)

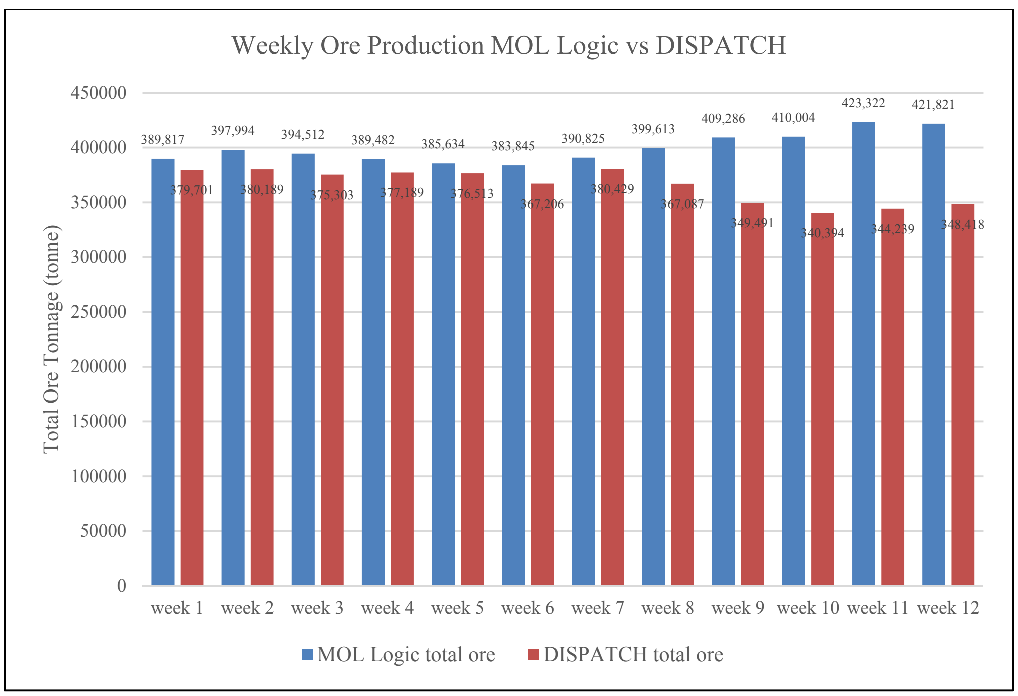

Figure 19: Total ore tonnage sent to the plants over 12 weeks of the operation (a comparison of MOL with DISPATCH)

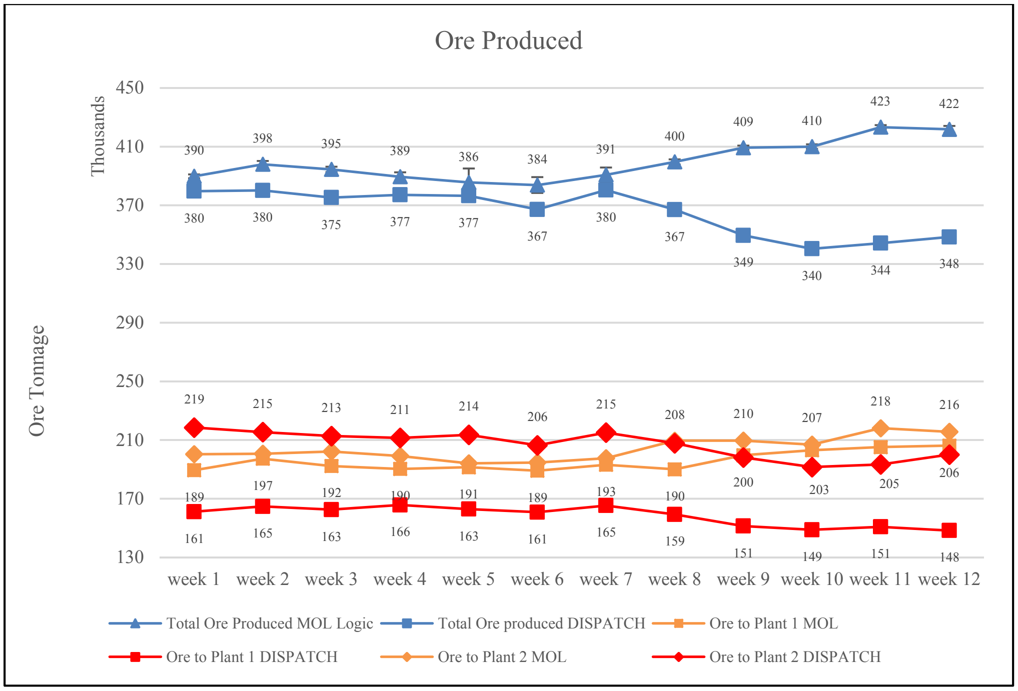

Figure 20: Ore sent to each processing plant and total ore produced over 12 weeks of the operation (MOL logic vs. DISPATCH)

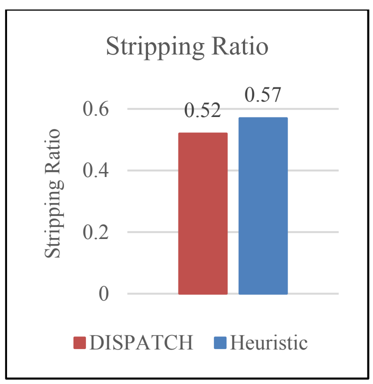

Figure 21: Stripping Ratio for the material removed in the period of 91 days.

To sum up, results of the study show three major improvements in the production of the case study (Gol-E-Gohar Iron Mine) where DISPATCH was substituted with the heuristic developed by MOL to handle truck dispatching. First of all, the study shows about 10% improvement in total tonnage extracted from the mine over the operation period of three months. Previous studies in the literature proved that implementing DISPATCH in a mining operation improves the production by somewhere between 10 to 15 % in different case studies (Kolonja & Mutmansky, 1993; White & Olson, 1986) in comparison with the fixed truck allocation. As a result, having 10% improvement in production of an operation using DISPATCH means having total improvement of 20 to 25% comparing with the operation with trucks locked to each shovel that has been used as a benchmark model for almost all of the studies addressed in the literature of truck dispatching (Ataeepour & Baafi, 1999; Bonates & Lizotte, 1988; Hashemi & Sattarvand, 2015; Kolonja & Mutmansky, 1993; Y. Lizotte, et al., 1987; Olson, et al., 1993; Soumis, et al., 1989; Temeng, Otuonye, & Frendewey, 1997; White & Olson, 1986). Second advantage of the MOL heuristic over DISPATCH shown in the results of this study is more reliable feed balance in a multi plant mining operation. Using MOL heuristic instead of DISPATCH in a multiple ore destination operation dramatically improve balance in feeds delivered to each of the processing plants. As it was shown in this paper, in an operation with two processing plants with a distance of around 350 meters between plants, 30% difference in plant feed rates reduced to less than 5% by replacing DISPATCH with MOL heuristic. This improvement happens due to DISPATCH logical drawback of being a single plant algorithm. The third major resulted from this study is 5% improvement in the operation stripping ratio by substituting DISPATCH with MOL heuristic. The reason behind this improvement is preference of ore to waste to be produced when all the shovels are in demand with the same priority.

10. Conclusions and future work

A heuristic dispatching algorithm was developed in MOL to be used in open pit mining as a part of the operation fleet management system to handle truck dispatching. To verify the goodness of the algorithm, first a case study of an Iron ore mining operation was selected. Then, well-known and widely used Modular mining fleet management system (DISPATCH) was embedded into the system to be used as the benchmark model. Afterwards, simulation model was run with both of the truck dispatching systems for a time horizon of three months. Comparing the results show improvement in the key performance indicators of the system when DISPATCH is substituted by MOL heuristic. Higher tonnage of material removed, less variation in plant feed rates, higher stripping ratio, balance in plant feed rates in a multi plant mining operation were obtained by replacing DISPATCH with MOL heuristic. Moreover, the developed algorithm feeds the plants with a difference in feed rate of less than 5% between two plants which shows an improvement of 25 to 30%. Stripping ratio of the operation was also improved by 5%. However, there is a limitation to deal with: although capacity of the plants is not the bottle neck of this model, they need to be taken into account in future works.

11. References

[1] Ahangaran, Daryoush Kaveh, Yasrebi, Amir Bijan, Wetherelt, Andy, & Foster, Patrick. (2012). Real –time dispatching modelling for trucks with different capacities in open pit mines. *ARCH MIN SCI, 57*(1), 39-52.

[2] Akbari, A. D. , Osanloo, M. , & Shirazi, M. A. (2009). Minable reserve estimation while determining ultimate pit limits (UPL) under price uncertainty by real option approach (ROA). *ARCH MIN SCI, 54*(2), 321-339.

[3] Alarie, Stéphane, & Gamache, Michel. (2002). Overview of Solution Strategies Used in Truck Dispatching Systems for Open Pit Mines. *INT J MIN RECLAM ENV, 16*(1), 59-76.

[4] Ataeepour, N., & Baafi, E. Y. (1999). ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. *International Journal of Surface Mining, Reclamation and Environment, 13*(3), 125-129.

[5] Basu, A. J. (1999). SIMULATION OF A LARGE OPEN PIT MINE OPERATION IN AUSTRALIA. *Mineral Resources Engineering, 08*(02), 157-164.

[6] Bellman, R. (1954). The theory of dynamic programming. *Bulletin of the American Mathematical Society 60*(6), 503-517.

[7] Bogert, J. R. (1964). Electronic eyes and ears monitor pit operations. *Met. Min. Process*, 42-45.

[8] Bonates, Eduardo, & Lizotte, Yves. (1988). A computer simulation model to evaluate the effect of dispatching. *International Journal of Surface Mining, Reclamation and Environment, 2*(2), 99-104.

[9] Burt, C. N., & Caccetta, L. (2007). Match factor for heterogeneous truck and loader fleets. *International Journal of Mining, Reclamation and Environment, 21*(4), 262-270.

[10] Caterpillar. (2016). CAT® MINESTAR™. Peoria, IL, USA.

[11] Dantzig, G.B. (1951). Maximization of A Linear Function of Variables Subject to Linear Inequalities. In Tjalling Charles Koopmans (Ed.), *Activity analysis of production and allocation* (pp. 404). the University of California: Wiley.

[12] Devex. (2016). Smartmine®. Belo Horizonte, Brasil.

[13] Forsman, B., Rönnkvist, E., & Vagenas, N. (1993). Truck dispatch computer simulation in Aitik open pit mine. *International Journal of Surface Mining, Reclamation and Environment, 7*(3), 117-120.

[14] Gove, D., & Morgan, W. (1994). *Optimizing Truck-Loader Matching*. Paper presented at the SME Annual Meeting.

[15] Hashemi, AliSaadatmand, & Sattarvand, Javad. (2015, 2015/01/01). *Application of ARENA Simulation Software for Evaluation of Open Pit Mining Transportation Systems – A Case Study.* Paper presented at the 12th International Symposium Continuous Surface Mining, Aachen.

[16] He, Ming-Xiang, Wei, Jiu-Chuan, Lu, Xin-Ming, & Huang, Bao-Xiang. (2010). The genetic algoritm for truck dispatching problems in surface mine. *ITJ, 9*(4), 710-714.

[17] Jaoua, A., Riopel, D., & Gamache, M. (2009). A framework for realistic microscopic modelling of surface mining transportation systems. *International Journal of Mining, Reclamation and Environment, 23*(1), 51-75.

[18] Kolonja, B., & Mutmansky, J. M. (1993). *Analysis of Truck Dispatching Strategies For Surface Mining Operations Using SIMAN*. Paper presented at the SME Annual Meeting.

[19] Krause, a, & Musingwini, C. (2007). Modelling open pit shovel-truck systems using the Machine Repair Model. *J. South. Afr. Inst. Min. Metall., 107*(8), 469-476.

[20] Leica Geosystems. (2016). Jmineops Fleet Management. Tucson, AZ, USA.

[21] Li, Z. (1990). A methodology for the optimum control of shovel and truck operations in open-pit mining. *Int J Min Sci Technol, 10*(3), 337-340.

[22] Lizotte, Y., Bonates, E., & Leclerc, a. (1987). *A design and implementation of a semi-automated truck/shovel dispatching system.* Paper presented at the 20th APCOM.

[23] Lizotte, Yves, & Bonates, Eduardo. (1987). Truck and shovel dispatching rules assessment using simulation. *Int J Min Sci Technol, 5*(1), 45-58.

[24] Micromine. (2009). Pitram Mining Solutions. Micromine Pty Ltd, Drupal Perth, WA, Australia.

[25] Modular Mining Systems. (2016). DISPATCH Fleet Management. Tucson, AZ, USA.

[26] Mueller, E.R. (1977). Simplified dispatching board boosts truck productivity at Cyprus Pima. *MIN ENG-LITTLETON, 29*(8), 40-43.

[27] Olson, J. P., Vohnout, S. I., & White, J. (1993). On improving truck/shovel productivity in open pit mines. *CIM Bulletin, 86*(973), 43-49.

[28] Oraee, Kazem, & Goodarzi, A. (2007). *General approach to distribute waste rocks between dump sides in open cast mines*. Paper presented at the Sixteenth international symposium on mine planning and equipment selection.

[29] Que, Sisi, Anani, Angelina, & Awuah-Offei, Kwame. (2016). Effect of ignoring input correlation on truck–shovel simulation. *International Journal of Mining, Reclamation and Environment, 30*(5-6), 405-421.

[30] Rockwell Automation. (2016). Arena Simulation Software (Version 14.7). Austin, TX, USA.

[31] Soumis, F., Ethier, J., & Elbrond, J. (1989). Truck dispatching in an open pit mine. *International Journal of Surface Mining, Reclamation and Environment, 3*(2), 115-119.

[32] Subtil, R. F., Silva, D. M., & Alves, J. C. (2011). A Practical Approach to Truck Dispatch for Open Pit Mines. *35th APCOM*(September), 765-777.

[33] Tabesh, Mohammad, Azimi, Ebrahim, & Askari-nasab, Hooman. (2012). *Linking Mine Production to Milling and Concentrate using Discrete Event Simulation* (No. 9781551953014). Edmonton, Canada: University of Alberta.

[34] TATA consultancy services. (2016). Dynamine. India.

[35] Temeng, Victor a, Otuonye, Francis O., & Frendewey, James O. (1997). Real-time truck dispatching using a transportation algorithm. *INT J MIN RECLAM ENV, 11*(4), 203-207.

[36] Temeng, Victor a, Otuonye, Francis O., & Frendewey, James O. (1998). A non preemptive goal programming approach to truck dispatching in open pit mines. *MRE, 7*(2), 59-67.

[37] Topal, Erkan, & Ramazan, Salih. (2012). Mining truck scheduling with stochastic maintenance cost. *J. Coal Sci. Eng., 18*(3), 313-319.

[38] Upadhyay, S. P., & Askari-Nasab, H. (2016). Truck-shovel allocation optimisation: a goal programming approach. *Min Tech*, 1-11.

[39] Wang, Qiang, Zhang, Ying, Chen, Chong, & Xu, Wenli. (2006). *Open-Pit Mine Truck Real-time Dispatching Principle under Macroscopic Control*. Paper presented at the Proceedings of the First International Conference on Innovative Computing, Information and Control - Volume 1.

[40] Wenco Mining Systems. (2013). Wencomine. Richmond, BC, Canada.

[41] White, J. W., & Olson, J. P. (1986). Computer-based dispatching in mines with concurrent operating objectives. *MIN ENG-LITTLETON, 38*(11), 1045-1054.

Uncertainty Based Short Term Planning in Open Pit mines – Simulation Optimization Approach

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Abstract

Accuracy in predictions leads to better planning and substantial gains by minimal opportunity lost over the course of execution. In open pit mining context, the complexity of operations coupled with highly uncertain and dynamic production environment, poses a limitation on accurate predictions and forces reactive planning approach to mitigate the deviations from what was planned. A simulation optimization framework/tool is presented in this paper to account for uncertainties in mining operations for best possible short term production planning and taking actions proactively during the planning process. The simulation optimization framework/tool uses a discrete event simulation of mine operations, which interacts with a goal programming based mine operational optimization tool (MOOT), to capture the performance and develop uncertainty based short term schedule. This framework through scenario analysis allows the planner to take proactive decisions to achieve the operational and long term objectives of the mine. This paper details the development of simulation and optimization models and presents the implementation of the framework on an iron ore mine case study for the verification through scenario analysis.

1. Introduction

Planning is a critical component of any successful execution to achieve desired results. Accurate predictions of the outcome serve as the backbone of any planning activity. This paper aims at presenting an approach where discrete event simulation in conjunction with an optimization tool is used for accurate prediction based efficient short term mine production planning. This paper describes how a detailed mine operational discrete event simulation model can be developed, keeping it flexible enough for easy scenario analysis and re-usability over the course of mine life, along with modeling techniques for truck haulage, haulage road network and interaction with external intelligent decision support systems for operational decision making. The proposed simulation optimization framework works in a bottom up approach by simulating the operations to generate short term plans. The external decision support system used is a mine operational optimization tool (MOOT) which provides shovel allocation decisions based on strategic schedule, thus linking operations directly with strategic schedule to generate uncertainty based short term plans.

Open pit mines usually have very large operations consisting of a number of equipment and years in mine life. Huge capital investments, bulk production demand and market dynamics have made it imperative for mining industries to focus on best and efficient mining practices to sustain in the market over the mine life. This makes planning a very critical process which is carried out in stages, as strategic plans, short term plans and operational plans based on the planning time horizon. The main objectives of short term plans are to achieve operational objectives of quality and quantity requirements of process plants and maximum utilization of equipment, and a high

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level of compliance with the strategic plans. The compliance of short term plans through operational executions is essential for compliance of strategic plans and in turn achieving economic objectives of the mine. Also, optimal equipment planning can only be realized with efficient utilization of all the assets involved during operations. Optimal use of available equipment is also essential to realize the strategic economic objectives, as approximately 60% of total operating cost in open-pit mines is accounted to truck and shovel operations. The whole planning process to achieve organizational objectives may go void if short term and operational planning are inefficient to reflect back. Short term planning thus may be regarded as very critical in achieving both operational objectives and strategic targets of the mine.

Malhotra and List (1989) describes the various complexities and challenges faced by the planners in short term planning process, whereas in another paper Henderson and Turek (2013) stress the plans to be as realistic as possible so that expectations can be delivered. Complexities in planning are usually dealt with assumptions, but such assumptions must be small and should not affect the practicality of the plans developed. Practicality of short term plans is a big problem which poses limitation on its achievability and the realization of operational objectives during executions. L'Heureux et al. (2013) proposed a detailed mathematical optimization model for short term planning for a period of up to three months by incorporating operations in detail. Gholamnejad (2008) proposed a binary integer programming model to solve the short term mine scheduling problem. Similar models have been proposed by Eivazi and Askari-Nasab (2012), Gurgur et al. (2011), Kumral and Dowd (2002) and others for short term mine planning accounting for various required details such as incorporating multiple destinations, precedence requirements and also incorporating multiple competing objectives. Although some of the existing models incorporate various details of the operations, they does not account for the uncertainties involved. Also the fixed nature of production rates from shovels and the tonnage haulage capacity by trucks poses a limitation on the achievability of the generated schedule, which depends greatly on the haulage profile, available number of trucks in the system, and also the truck dispatching efficiency. Practical applicability or achievability of the schedules is a major limitation observed in most models. A practical short term plan would be one which accounts for the shovel movement times and production lost during such movements between faces, equipment failures, equipment availabilities, real time grade blending and fluctuations, and changing rates of production from shovels based on their locations, available trucks, haul road gradients and truck dispatching efficiency.

Simulation models also find a large scope in mining industry and are being used widely for prediction based decision making for specific problems. Sturgul (1999) reviews the application of simulation in mining in United States and credits Rist (1961) for the first published application of computer simulation in mining. Kolonja and Mutmansky (1994), Ataeepour and Baafi (1999) and many others used simulation to prove the positive impact of truck dispatching strategies in mining. Awuah-Offei et al. (2003) and Upadhyay et al. (2013) used simulation to determine optimal number of truck and shovel requirement in open pit mines. Similarly Yuriy and Vayenas (2008) applied simulation with a reliability assessment model to predict the impact of failures on production, availabilities and utilizations of equipment. Most of the simulation models on mining, published in literature, focus on specific problems and do not detail the development of the models as such. Also the models find very limited scope and are designed to tackle specific problems.

Modeling accurate truck haulage system is crucial to model realistic simulation of mine operations. Most simulation models, as noted by Jaoua et al. (2009), model the transportation system as a macroscopic process, which do not account for platoon formations and interaction of trucks on haul roads leading to decreased travel speeds. But at the same time, incorporating a real time control in a microscopic process to model accelerations and decelerations may be resource intensive. In most cases a faster truck slows down to the speed of a leading slower truck and travels in platoon if overtaking is not allowed, which is the case in most mining systems. Thus, inhibiting the overtaking, forcing the faster truck to move with the same speed as the leading slower truck may be considered sufficient to model the truck haulage system for the scale and objectives of the simulation model presented in this paper. It is also important to model the truck speeds based on haul road characteristics, as trucks don't travel with constant speed throughout the road network. The main parameters affecting the speed of trucks include: driver behavior, rimpull curve characteristics of trucks, haul road gradient and rolling resistances, and certain other factors related to safety such as visibility (day and night). The driver behavior is a critical factor which requires a thorough study before modeling it into the simulation. It was considered sufficient to model an average driver behavior for all trucks and thus not considered into modeling the process. The truck speeds, thus, are modeled based on rimpull curve characteristics of trucks and haul road characteristics in this paper.

Simulation optimization is a fairly new approach in mining industry. Fioroni et al. (2008) used simulation in conjunction with a mixed integer linear programming model to reduce mining costs by optimal production planning. Jaoua et al. (2012) used a simulation optimization approach to develop a simulation based real time control tool for truck dispatching. There is not so much application of this approach yet in mining industry, but it bears a great potential for developing robust tools for decision making purposes.

Most research in the area of short term and operational planning has been limited to mathematical programming based optimization techniques. But L'Heureux et al. (2013) observes that modeling a mining operation in detail by incorporating multiple periods, faces, shovel movements, truck allocations and plants poses a limitation on solvability due to the size of such models. Such models will be too big in size that even state of the art hardware and software will be unable to handle their complexity and size (Bjørndal*, et al.*, 2012). A simulation optimization approach provides a better alternative to handle this problem, where less number of periods can be considered in mathematical optimization model, and more details can be incorporated within simulation models, thus providing an opportunity to incorporate all the operational details into the planning process. Also the proposed approach generates the short term schedule based on the simulated operations, and thus remains practical and achievable, while providing opportunity for proactive planning through scenario analysis.

This paper briefly presents a goal programming based tool MOOT for optimal operational decision making and details the development of a discrete event simulation model in Arena which is flexible and reusable over time. The emphasis is given to modeling techniques for haul road network, truck travel and an interaction mechanism to communicate with external decision support system (MOOT) for optimal shovel and truck allocation decision making. The rest of the paper is structured as follows: the simulation optimization framework is presented first which describes the overall approach, followed by MOOT and a detailed development of the simulation model. The implementation of the simulation optimization model is then presented on a case study, followed by discussion and conclusions.

2. Simulation optimization framework

The overall framework of this research is presented in Fig. 1, which shows the application of an intelligent operational decision making tool (MOOT) for short term mine planning and in parallel for dynamic operational decision making in real mine operations. As mine operations are complex, a very intelligent MOOT would be required for a successful implementation of it in real mine operations, which can be carried out as a future research. The context of this paper is limited to the applicability of MOOT with a discrete event simulation model as simulation optimization approach for short term mine planning, the extent of modeling for which is considered satisfactory in this paper.

Fig. 1 show that for the short term mine planning, the strategic schedule and the designed haul road network are first translated into a configuration input file, which serves as input to the simulation model and MOOT. The configuration file is also updated with fitted distribution times based on the historical operational data. The model then simulates the operations for the planning horizon of the input schedule, interactively seeking shovel and truck allocation decisions from MOOT. The simulation data is then uploaded into the simulation database, which is then queried to fetch uncertainty based schedule and the observed KPIs of the mine operations. The observed achievability of the strategic schedule and the KPIs are then analyzed to run further scenarios, by improving poor performance processes, to develop best and practical short term schedule.

One major difference between the conventional mathematical optimization based short term planning process and the proposed simulation optimization approach is that planning in this approach is carried out by capturing the simulated operations. The conventional mathematical models optimize the overall operations for the planning period to generate a schedule which contains high level of uncertainty over higher periods, which is taken into account as real operations continues; and updated regularly. In the proposed simulation optimization approach, overall operations are optimized in a similar manner for a limited number of periods of the planning time horizon. But this approach also implements the generated schedule into the simulation to capture the uncertainty, and re-optimizes each time system state changes. This basic difference allows a planner to generate realistic schedules and take proactive decisions so that perceived deviations in operational and strategic objectives can be minimized.

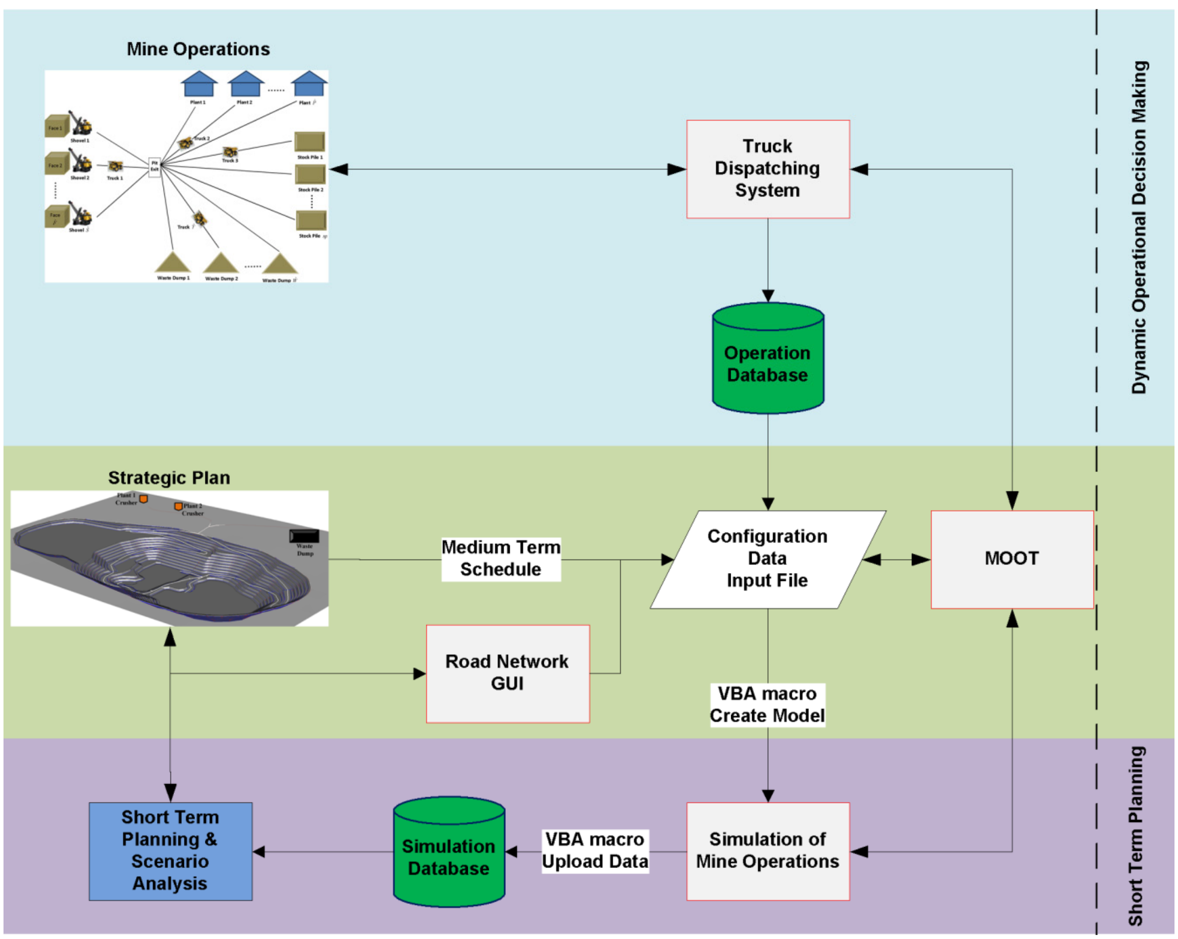

Fig. 1. Framework of the simulation optimization approach and the applicability of MOOT for short term mine planning and real time dynamic operational decision making

An efficient simulation model is a prime requirement in this approach, which needs to model the individual operational processes accurately and replicate the mining system. It is also essential in this approach that the simulation model is flexible and reusable over time, so that planning activities can be carried out over the mine life. Although overall mining system does not change over the mine life, the mine layout consisting of scheduled blocks, haul road design and equipment may change along with the process time distributions for various equipments. Thus Matlab (The MathWorks Inc.) and VBA based interfaces have been created to translate existing mine layout into simulation (Fig. 2**Error! Reference source not found.**). The truck travel process is also modeled in detail which captures the speeds based on rimpull curve characteristics of trucks and the haul roads, and any interaction between trucks while travelling leading to platoon formations.

3. Mine operational optimization tool (MOOT)

The main objective of mine operational optimization tool (MOOT) is to optimize the mine operations over a fixed number of periods such that operational objectives of maximum production and, quality and quantity requirements of plants can be achieved by providing truck allocations and shovel assignments within the mining faces provided by strategic schedule. Thus MOOT presented in this paper is developed as a mixed integer linear goal programming (MILGP) model to optimize multiple operational objectives following a non preemptive approach. This section presents the variables, objectives and constraints formulated to develop MOOT (see Appendix for the Indices and parameters used).

3.1. Variables

The MILGP model is constructed using 14 types of variables to incorporate various operational constraints and modeling objectives. Shovel allocations to faces is modeled using a binary assignment variable. Another binary variable is used to keep track of mined out faces over multiple periods. The movement of shovels is also controlled using the same assignment variable and the mined out variable. To model the continuous movement of shovel over two periods i.e. if a shovel starts movement in one period but ends in next period, another binary variable is used to keep track of remaining movement time in that period. Truck allocations are modeled for every truck type in the system using an integer variable. The remaining variables are continuous in nature and are used to model the production from faces, deviations in production from shovel, deviations in grades and tonnage at destinations, tonnage available at faces and movement times of shovels. All the variables considered in the model are explained in Table 1.

Table 1: Variables considered in the MILGP model (MOOT)

$a_{s,f,p}$	Assignment of shovel *s* to face *f* in period *p* (binary)
$m_{f,p}$	0 or 1 binary variable if face *f* is mined out in period *p*
$y_{s,p}$	0 if $r^{rem}_{s,p}$ is greater than 0, else 1
$n_{t,f,d}$	Number of trips made by truck type *t*, from face *f*, to destination *d* (integer) in first period
$x_{s,f,d,p}$	Fraction of tonnage at face *f* sent by shovel *s*, to destination *d* in period *p*
$x^{-}_{s,p}$	Fraction of maximum capacity of shovel *s* less produced in period *p*
$\delta^{-}_{d^c,p}, \delta^{+}_{d^c,p}$	Negative and positive deviation in production received at processing plants d^c in period *p*, as fraction of processing plant capacities
$g^{-}_{k,d^o,p}, g^{+}_{k,d^o,p}$	Negative and positive deviation in tonnage content of material type *k* compared to tonnage content desired, as per desired grade, at ore destinations d^o in period *p*

$l_{f,p}$	Tonnage of material available at face *f* at the start of period *p*
$r_{s,p}$	Movement time (minutes) for shovel '*s*' in period '*p*' to go to next assigned face
$r_{s,p}^{rem}$	Remaining movement time (minutes) to be covered in next period
$r_{s,p}^{act}$	Actual movement time (minutes) covered in period '*p*'

3.2. Goals

Although there can be various operational objectives, this model considers four main operational objectives as goals: (1) maximize production by minimizing the negative deviation in production by shovels compared to their capacities, (2) minimize the deviation in production received at processing plants compared to their capacities, (3) minimize the deviation in grades delivered to ore destinations compared to desired grades, and (4) minimize the movement times of shovels.

$$\Psi_1 = \sum_p \sum_s \left(\frac{1}{p}\right) \times x_{s,p}^{-} \tag{1}$$

$$\Psi_2 = \sum_{d^c} \sum_p \left(\frac{1}{p}\right) \times (\delta_{d^c,p}^{-} + \delta_{d^c,p}^{+}) \tag{2}$$

$$\Psi_3 = \sum_p \sum_{d^o} \sum_k \left(\frac{1}{p}\right) \times (g_{k,d^o,p}^{-} + g_{k,d^o,p}^{+}) \tag{3}$$

$$\Psi_4 = \sum_s \sum_p r_{s,p} \tag{4}$$

3.3. Objective function

The model is optimized using a non-preemptive approach, thus the four objectives considered in the model are normalized and combined as the weighted sum, given in Eq. (5). The weights assigned to individual objectives are based on the desired preference of the objective over others. The normalization of individual objectives is carried out by optimizing each objective separately to determine their values in pereto optimal space (Grodzevich & Romanko, 2006).

$$\Psi = W_1 \times \overline{\Psi}_1 + W_2 \times \overline{\Psi}_2 + W_3 \times \overline{\Psi}_3 + W_4 \times \overline{\Psi}_4 \tag{5}$$

Where:

$$\overline{\Psi}_i = \left(\Psi_i - Utopia_i\right) / \left(Nadir_i - Utopia_i\right) \tag{6}$$

3.4. Constraints

The constraints in the model are formulated to model the shovel assignments constrained by precedence requirements, movements, production by each shovel, production received at process plants, grades received at ore destinations and the number of truck trips required by each truck type.

$$\sum_s a_{s,f,p} \le 1 \qquad \forall f \;\&\; \forall p \tag{7}$$

$$a_{s,Fi_s,p} = 1 \qquad \forall s \;\&\; p = 1 \tag{8}$$

$$\sum_f a_{s,f,p} \le 2 \qquad \forall s \;\&\; \forall p \tag{9}$$

$$\sum_f a_{s,f,p} \le a_{s,f,p} + m_{f,p} + (1-a_{s,f,p-1}) + (1-a_{s,f,p}) \times BM \qquad \forall s, \forall f, \forall p \tag{10}$$

$$a_{s,f,p+1} \ge a_{s,f,p} - m_{f,p} \qquad \forall s, f, p = 1...P-1 \tag{11}$$

$$a_{s,f,p+1} \le 1 + a_{s,f,p} - m_{f,p} \qquad \forall s, f, p = 1...P-1 \tag{12}$$

$$a_{s,f,p+1} \ge 2 \times a_{s,f,p} - \sum_f a_{s,f,p} \qquad \forall s, f, p = 1...P-1 \tag{13}$$

$$r_{s,p} \ge \sum_{f^1} a_{s,f^1,p} \times \Gamma^F_{f^1,f} \big/ S_s - (1-a_{s,f,p}) \times BM \qquad \forall s, \forall f \;\&\; p \tag{14}$$

$$r_{s,p} = r^{act}_{s,p} + r^{rem}_{s,p} \qquad \forall s \;\&\; \forall p \tag{15}$$

$$r_{s,p} \le \left(\sum_f a_{s,f,p} - 1 \right) \times BM \qquad \forall s \;\&\; \forall p \tag{16}$$

$$\sum_d x_{s,f,d,p} \le \left(1 - a_{s,f,p} + a_{s,f,p-1}\right) \times BM + y_{s,p} \times BM \qquad \forall s, \forall f \;\&\; \forall p \tag{17}$$

$$r^{rem}_{s,p} \ge \left(1 - y_{s,p}\right) \times \left(2 \times \varepsilon\right) \qquad \forall s \;\&\; \forall p \tag{18}$$

$$r^{rem}_{s,p} \le y_{s,p} \times \varepsilon + \left(1 - y_{s,p}\right) \times BM \qquad \forall s \;\&\; \forall p \tag{19}$$

$$\sum_f \sum_d x_{s,f,d,p} \times O_f + \left(r^{rem}_{s,p-1} + r^{act}_{s,p}\right) \times 60 \times X_s \big/ L_s \le T \times 3600 \times X_s \times \alpha^S_s \big/ L_s \qquad \forall s \;\&\; \forall p \tag{20}$$

$$l_{f,p} = O_f \qquad \forall f \;\&\; p = 1 \tag{21}$$

$$l_{f,p+1} = l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \qquad \forall f \;\&\; p = 1...P-1 \tag{22}$$

$$l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \ge \left(1 - m_{f,p}\right) \times \left(O_{\min} + \varepsilon\right) \qquad \forall f \;\&\; \forall p \tag{23}$$

$$l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \le m_{f,p} \times O_{\min} + \left(1 - m_{f,p}\right) \times BM \qquad \forall f \;\&\; \forall p \tag{24}$$

$$m_{f,p+1} \ge m_{f,p} \qquad \forall f \;\&\; p = 1...P-1 \tag{25}$$

$$\sum_d \sum_f x_{s,f,d,p} \times O_f \big/ X^+_s + x^-_{s,p} = 1 \qquad \forall s \;\&\; \forall p \tag{26}$$

$$\sum_d x_{s,f,d,p} \le a_{s,f,p} \qquad \forall s, \forall f \;\&\; \forall p \tag{27}$$

$$\sum_s \sum_{d^o} x_{s,f,d^o,p} \times O_f \le l_{f,p} \times Q_f \qquad \forall f \;\&\; \forall p \tag{28}$$

$$\sum_s \sum_{d^w} x_{s,f,d^w,p} \times O_f \le l_{f,p} \times (1 - Q_f) \qquad \forall f \;\&\; \forall p \tag{29}$$

$$N^F_f \times \sum_s a_{s,f,p} - \sum_{f'} m_{f',p} \le 0 \qquad \forall f, \forall p \;\&\; f' \in PrecedenceSet_f \tag{30}$$

$$\sum_s \sum_f x_{s,f,d^c,p} \times O_f \Big/ \left(Z_{d^c} \times T \right) + \delta^-_{d^c,p} - \delta^+_{d^c,p} = 1 \qquad \forall d^c \ \& \ \forall p \tag{31}$$

$$\delta^-_{d^c,p} \le \Lambda^-_{d^c} \Big/ Z_{d^c} \qquad \forall d^c \ \& \ \forall p \tag{32}$$

$$\delta^+_{d^c,p} \le \Lambda^+_{d^c} \Big/ Z_{d^c} \qquad \forall d^c \ \& \ \forall p \tag{33}$$

$$\sum_s \sum_f x_{s,f,d^o,p} \times O_f \times \bar{G}_{f,k} + g^-_{k,d^o,p} - g^+_{k,d^o,p} = \sum_s \sum_f x_{s,f,d^o,p} \times O_f \times G_{k,d^o} \qquad \forall k, \forall d^o \ \& \ \forall p \tag{34}$$

$$\sum_s x_{s,f,d,p} \times O_f \le \sum_t n_{t,f,d} \times H_t \qquad \forall d, \forall f \ \& \ p = 1 \tag{35}$$

$$\sum_s x_{s,f,d,p} \times O_f + J \ge \sum_t n_{t,f,d} \times H_t \qquad \forall d, \forall f \ \& \ p = 1 \tag{36}$$

$$\sum_d n_{t,f,d} \times H_t \le \sum_s \left(\sum_d x_{s,f,d,p} \times O_f + a_{s,f,p} \times J \right) \times M^t_{t,s} \qquad \forall t, \forall f \ \& \ p = 1 \tag{37}$$

$$\sum_f \sum_d n_{t,f,d} \times \bar{T}_{t,f,d} \le T \times 60 \times N^T_t \times \alpha^T_t \qquad \forall t \tag{38}$$

$$\sum_f \sum_d x_{s,f,d,p} \le \left(1 - \phi_s\right) \times BM \qquad \forall s \ \& \ p = 1 \tag{39}$$

$$a_{s,f,p} \le \min\left(1, abs\left(M^{ore}_s - Q_f\right)\right) \qquad \forall s, \forall f \ \& \forall p \tag{40}$$

The assignment of shovels to faces is modeled by constraints (7) to (13). The model assigns shovels to their initial faces in the first period by constraint (8), and limits only one shovel to be working on any face in any period by constraint (7). Constraint (9) is used to model the shovel movement to a new face within the same period, which limits a shovel be allocated to maximum two faces during any period. Constraint (10) looks over all the available faces and limits the maximum number of faces assigned to a shovel in a period to two, only if one of the assigned faces is mined out completely, otherwise limits it to one. The right hand side of this constraint takes a very large value for all the faces where shovel is not assigned by using a very large value (BM), and does not do anything. For the faces shovel is assigned, constraint looks at the assignment in the previous period, which if false constraint behaves similar to constraint (9). If the shovel is found to be assigned to the face in previous period, constraint now looks if that face is mined out completely by that period, which if true shovel is allowed to be assigned to two faces otherwise shovel is allowed to be assigned to maximum one face in that period. The continuity in shovel assignment is incorporated by constraint (11), which forces the shovels to remain on the same face in next period if the face is not mined out completely by that period. Constraint (12) prohibits a shovel to be assigned to a new face which is already mined out. It however lets a shovel sit on a face where that shovel was working in previous period. Constraint (13) works in conjunction with constraint (11) to model the specific case when a face is mined out towards the end of a period and the remaining time is not sufficient to complete the movement of shovel to the new face. In such a case, without this constraint, model finds flexibility to assign the shovel to the new face in the next period, without modeling the movement. Thus constraint (13) is used to force any shovel which was working only on one face during any period to remain on the same face in the next period, in turn forcing the model to capture and start shovel movement in the previous period itself.

Shovel movement times are modeled using constraints (14) to (19). Constraint (14) models the movement time of a shovel in a period. Due to the dimensionality of the variables considered, this constraint could not be formulated as equality. Thus constraint (14) models the movement time as greater than or equal to the actual movement time, which takes the equality value because model want the minimum movement time in the objective function. The constraint looks over all the faces and right hand side of the constraint takes a negative value for all the faces shovel is not assigned to. The right hand side takes a positive value only for two faces where shovel is actually assigned. If shovel is only assigned to one face in a period, right hand side takes a value of zero for the assigned face, thus no movement time during that period.

The movement time is further split into actual time spent in movement during that period and remaining movement time for the next period by constraint (15). Constraint (16) ensures a zero movement time if shovel was assigned to only one face in a period. Constraints (17) to (19) prohibit any production from the assigned faces if remaining movement times are not zero, i.e. if shovels have not moved to them completely in that period.

The total production capacity of the shovels is modeled by constraint (20), limited by the time lost during movement and maximum production possible by the shovels. Constraints (21) to (25) model the tonnage available at faces in each period and sets value to the mined out binary variable for each face.

Production by shovels is modeled by constraints (26) to (29). Constraint (26) models the negative deviation in production by shovel compared to its capacity and constraint (27) do not allow any production from a face where the shovel is not assigned during that period. Constraint (28) and (29) model the maximum ore and waste production possible from the assigned faces.

The accessibility of faces is modeled using the precedence requirement by constraint (30), which lets an assignment variable of a face to take a value of one, only if all the precedence faces are already mined out by that period.

The deviation in production received at processing plants, compared to capacity, is modeled by constraint (31), and limited by constraints (32) and (33). Constraint (34) models the deviation in grades received at ore destinations in the form of deviation in metal content received.

Truck allocation is required only for the decision time frame (first period) which is used within the simulation. Thus only first period of the optimization is considered for truck allocations. The required number of truck trips is modeled using constraints (35) to (38). As production is not always an integer multiple of truck capacities and to induce a flexibility in the production, Constraint (35) and (36) determine the required number of truck trips to haul the produced tonnage. Constraint (37) is similar to constraint (36), but it also models the matching of truck types to shovels, i.e. no trip is possible by a truck type from a face where a non matching shovel is assigned. Constraint (38) models the maximum number of truck trips possible based on the number of trucks and production time available.

Constraint (39) is used to indicate shovel failures to the model when running with the simulation. It lets shovel sit on the face but forces zero production from the assigned face in the first period (the decision time frame for simulation), assuming shovel will be back from next period. Shovels can also be locked to work only in ore or waste or allowed to work in both using Constraint (40).

4. Discrete event simulation

The discrete event mine simulation model is developed in Arena . The VBA capability of Arena has been extensively used to build the simulation model and update the existing layout of the mining system. Fig. 2 shows the steps which are carried out in the simulation. Step 1 is a manual process which is carried out only if the mining system changes i.e. road network, schedule, number of shovels and number of truck types and shovel types in the system changes. A Matlab based GUI is created which reads the dxf file of the designed haul road to generate readable input for Arena, which is then used by a VBA macro written in Arena to generate the haul road network within the simulation model. The same VBA macro also reads other system characteristics from a common configuration input file to build various variables, expressions, shovel resources and truck transporter resources. After the model is manually built, rest of the system does not require any manual operation. General system characteristics such as number of trucks of each type, capacities of equipment, process times and distributions can be readily changed into the common configuration input file which remains linked to Arena, making the model flexible enough for easy scenario analysis.

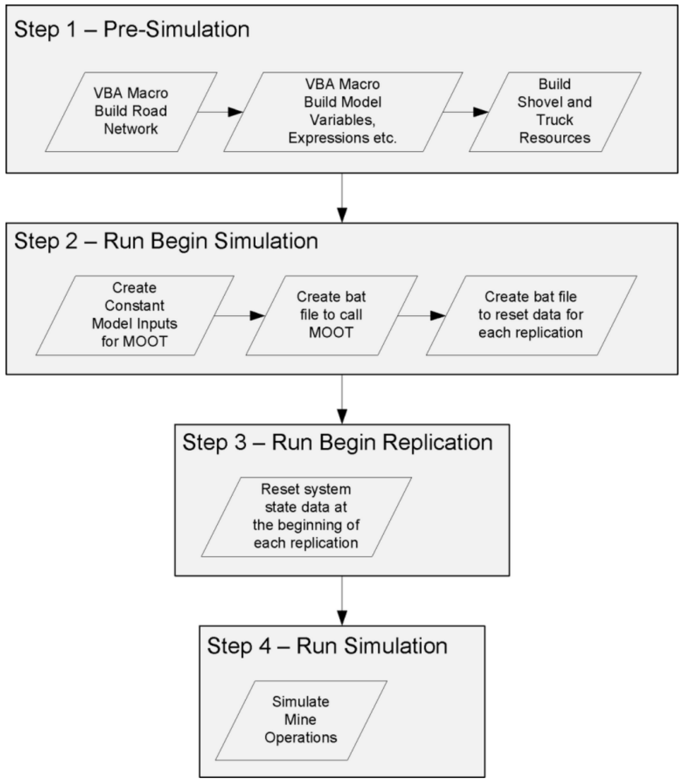

Fig. 2: Steps for translating the existing mining layout into the model and simulation run

Once the simulation model is run, at the beginning of the simulation before compiling the model, a Matlab function is run through the VBA in Arena to read and create a constant parameter matrix from the common input configuration file, which is used by MOOT for decision making purposes. This is necessary because once the simulation is under process the input configuration file becomes inaccessible from outside Arena. Also this reduces the run time of MOOT for reading the inputs from the external file each time it is run. The second step also creates bat files for calling the Matlab functions to run MOOT and resetting the schedule at the end of each replication. The interaction between MOOT and Arena occurs through VBA and text files. The current state of the system including the available tonnage at faces, current face of working of each shovel and shovel states are provided as input to MOOT through a text file and the output of MOOT is also returned through a text file.

Step 3 occurs after the simulation model is compiled just before the start of simulation, and each time a new replication starts. At this step the system state is re-initialized, i.e. shovel positions are reset to their initial faces in the schedule and the tonnages of polygons are reset to their original values. The simulation model is then run in step 4 for multiple replications to capture the mining operational data.

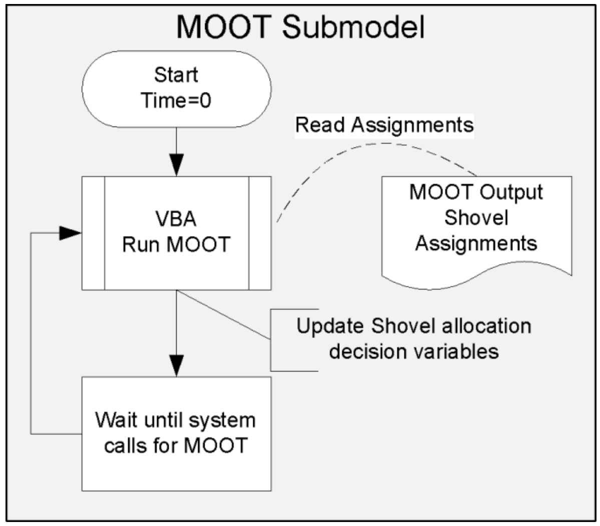

Fig. 3: Submodel to call MOOT as external decision support system for shovel and truck allocations optimization

Fig. 3 shows a submodel for running the external decision support system MOOT. This model is run in the beginning of each replication at simulation time of zero and each time the system state changes, i.e. a shovel comes up after failure or any face gets depleted. The MOOT is called through VBA and its outputs are read-in to reassign shovels, target productions and number of truck trips by each truck type on various paths.

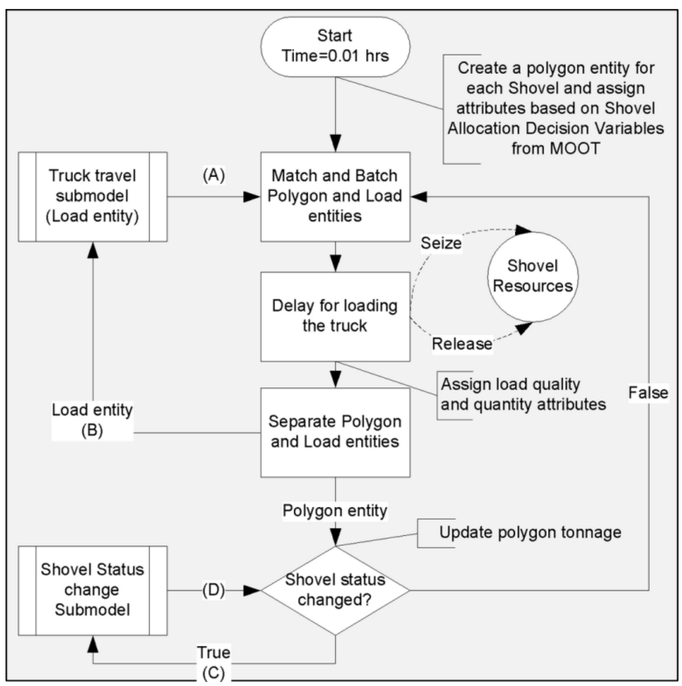

Fig. 4: Flow of the mine operation simulation model

Fig. 4 shows the flow of the main simulation model. This main model consists of a polygon (face) entity and a load entity. Polygon entities are created for each shovel in the system in the beginning of the simulation after MOOT output is recorded. Each of these polygon entities are then assigned the polygon attributes based on the shovel assignments provided by MOOT. Similarly a load entity is created for each truck and truck attributes are assigned to them after the MOOT is run in the beginning of simulation (Fig. 9). In the main model, once a load entity reaches a shovel, it is matched with the polygon entity of the corresponding shovel and batched together into a single entity temporarily to model the loading process at the shovels. Now the shovel resource is seized and loading is carried out based on the number of buckets, bucket cycle time distributions and the total tonnage for the shovel and truck type combination. Shovel resource is released after the loading process is finished and load quality, quantity and time attributes are assigned to the batch entity, which is then separated back into load and polygon entities carrying their respective attributes along with loading attributes. Load entity is then sent into the truck travel submodel where hauling, dumping and return travel of trucks back to shovel takes place. Polygon entities are updated with their remaining tonnages and then checked for any change of status, which includes if polygon is completely depleted, or corresponding shovel is failed, or put on standby (Fig. 8); otherwise it goes back to match process where shovel sits idle until next load entity (truck) arrives.

The dumping process is shown in Fig. 5. After the load entity gets its load from the polygon entity, it is transported to its assigned dump location by the truck transporters following the haulage road network. The haul road network, created in the beginning, contains dump points on the network based on the number of simultaneous dumps possible at each dump location. One of the dump points is then chosen based on number of trucks in queue at each dump point once a truck reaches its dump location. The trucks are then moved to the chosen dump point for the dumping process. If the dump location is a hopper, for the crushers, load entities wait until there is enough room for the dumping to take place, otherwise go directly for the dumping process where the load entities seize a dump location resource and carry out the dumping process with the dumping process time delays. Load entities then move back into the travel submodel to travel to an assigned shovel by the truck dispatching logic.

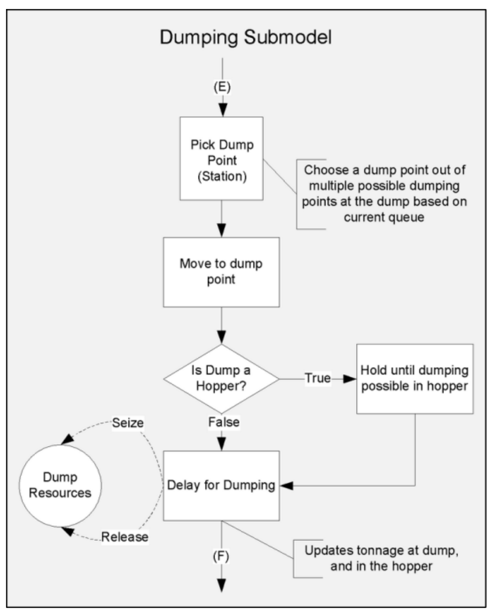

Fig. 5: Flow of the dumping submodel

Although processing plant operations are not modeled in detail into the simulation model, the flow out of hoppers into the crushers is critical to model the flow of ore from mining system into process plants. Thus process plants – flow out of hoppers submodel is created to model the continuous flow out-of hoppers (Fig. 6). The hoppers in the simulation are modeled as tanks containing regulators to remove material out into further processes which are not modeled here. This submodel creates a flow entity for each hopper in the system at the start of simulation and assigns hopper attributes. The entities are then duplicated. The flow entities then seize the regulators for corresponding hoppers and start removing material continuously out of hoppers based on crusher capacities until the end of replication when they release the regulators and get disposed. The duplicated flow entities are looped with fixed delays to record the periodic statistics at the hoppers.

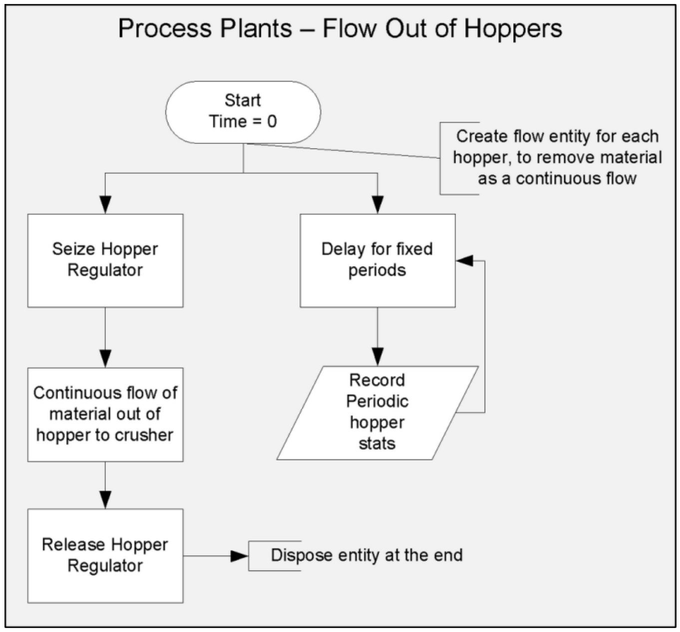

Fig. 6: Flow of the process plant submodel

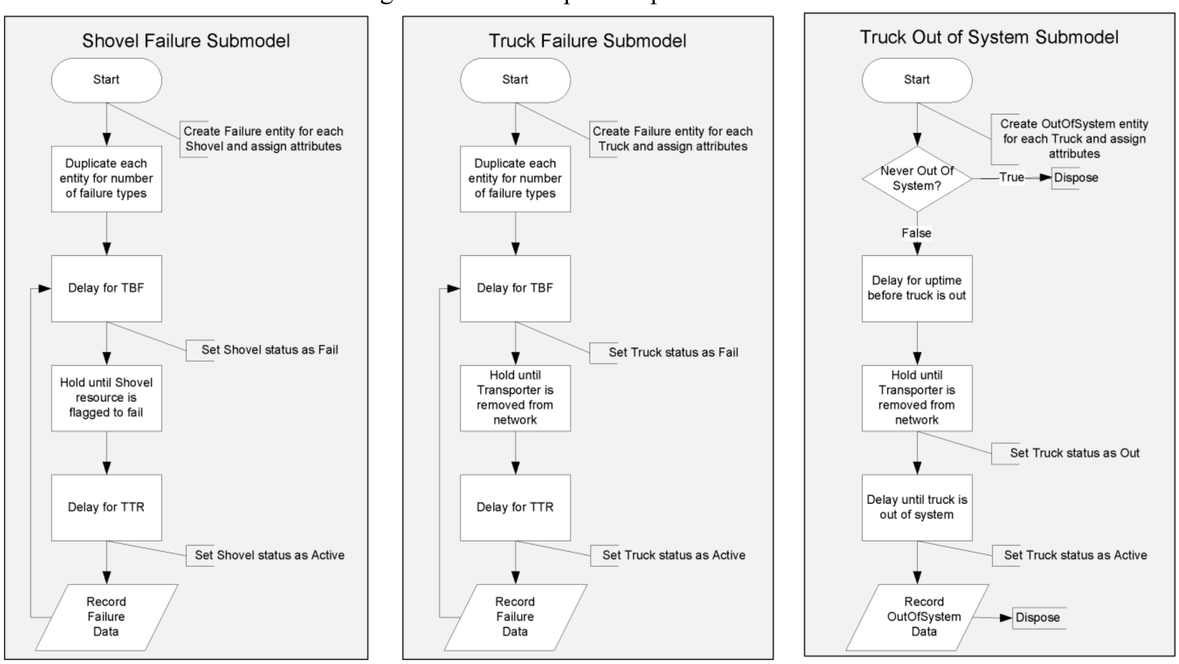

Fig. 7: Shovel and truck failure submodels and truck out of system submodel

Shovel and truck failures and truck out of system based on schedule are modeled separately, as shown in Fig. 7. Truck and shovel resources are failed in these submodels, after which they are removed from the main simulation logic of Fig. 4. A failure entity is created for each shovel and each truck in the system at the start of simulation in both shovel and truck failure submodels respectively. The entities are then duplicated for number of failure types. Time between failures (TBF) and time to repair (TTR) are then determined based on failure time distributions. Entities then wait for TBF after which truck or shovel status is changed to fail. Then entities wait until actual truck or shovel resource is taken out of main simulation logic, after which entities are delayed for the repair time (TTR) and status is changed back to active. The actual resources are then taken back into operation in the main simulation logic as the status is changed to active. Truck out of system submodel is developed in the similar fashion, but as it follows a fixed schedule it is modeled separately. In this submodel out of system entities are created at the start of replication and assigned the start and end times for the scheduled out of system for each truck. If any truck does not have any out of system hours scheduled, the corresponding entities are disposed off right away, otherwise they are delayed until the start of scheduled out of system, and the truck status is changed as out of system to intimate the main simulation logic to remove the truck from operation. The out of system entity then waits until actual truck resource is removed from the main logic and then delayed until the end of scheduled out of system when the truck status is changed back to active and the entity is disposed after recording the out of system times data.

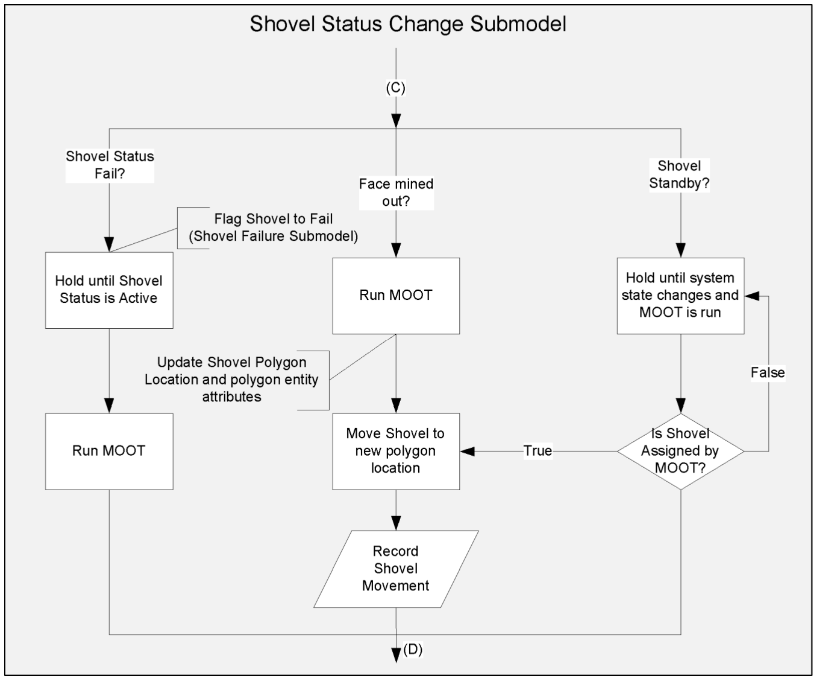

Fig. 8: Flow of shovel status change submodel controlling shovel failures, standby, and reallocation

Fig. 8 shows shovel status change submodel which models the shovel movements, standby and failures in the main simulation logic. After each truck load the status of shovel is checked if it is ready to go for the next load. If the material at the assigned face is depleted, or shovel is not assigned to work (standby) or failed then polygon entity is moved into shovel status change submodel. If the shovel status is 'fail', it is flagged as failed in the main logic to start failure time in the failure submodel. The polygon entity waits until shovel status is changed back to active in the failure submodel, after which MOOT is called again to re-optimize the system and reassign faces and target productions for all the shovels. If status change of shovel is because the material of the polygon entity is completely depleted, MOOT is called to re-optimize and assign new face to the shovel. After which polygon attributes are updated to new face assignment and shovel is delayed for the movement time to the new face and shovel movement is recorded. If instead a shovel is not assigned to work, i.e. MOOT output assigns zero target production to a shovel, corresponding polygon entity waits until system is re-optimized by MOOT. Each time MOOT is run, polygon entities waiting as standby are checked if corresponding shovels are assigned to work. If they remain on standby, corresponding polygon entities continue to wait for the next optimization, otherwise shovel is moved to the newly assigned face and movement data is recorded. The polygon entities then move and wait for a truck to arrive.

4.1. Truck haulage

Trucks in the simulation model are modeled as guided path transporters in Arena. Guided path transporters are provided in Arena to model the AGVs (automated guided vehicles), which are restricted to travel on fixed paths, by seizing and releasing the zones of length equal in length of the

AGVs. This characteristic allows us to model the traffic congestions and platoon formations of trucks on haul roads, as overtaking is prohibited for AGVs.

The haul road network of the mine is created as Network consisting of unidirectional network links. To model two way haul roads with single lanes, unidirectional network links are duplicated in opposite direction to model the upcoming travel paths. Each network link connects two points on the haul road and is divided into number of zones. Trucks are moved zone by zone in Arena by seizing the next zone and releasing the occupied zone. This seizing and releasing process restricts the movement of trucks and do not allow the trailing trucks to overtake. To incorporate a safety distance between trucks while traveling, zones of length equal to the summation of average truck length and a safety distance are constructed. By selecting the zone control rule as 'start', transporters are made to release a zone when next zone is seized and thus safety distance is maintained between trucks.

A Matlab GUI is created which reads the dxf input of the designed haul road network and converts into a formatted input, which is then used by the VBA in Arena to construct the Network, Network Links and zones. This instills flexibility into the model to change the haul road network very easily over the course of mine life.

In Arena, transporters or the entity seizing the transporter remain out of the main logic when travelling and thus cannot be controlled unless they reach their destination. Thus, although transporters in arena can be sent directly from its position to any other position on the Network, trucks in this simulation model are moved link by link on the haul roads. This is done to assign speed to trucks based on varying haul road characteristics, model the truck failures and have control at least intermittently while travelling. The modeling of truck haulage logic of mine operations is shown in Fig. 9, which is designed to move the trucks link by link on their path to respective destinations and keep a control on their movement.

Fig. 9 shows the truck travel submodel logic and the initialization logic for the trucks in the model. At the start of simulation, after MOOT has provided shovel and truck allocation decision, a load entity is created for each truck in the system and truck attributes are assigned to them. These load entities are then assigned a shovel using a truck dispatching logic and following truck allocation decision given by MOOT. A transporter is then allocated to each load entity and dispatched directly to their assigned shovel stations on the haul road network. Entities then travel out of the main logic through the haul road network with the transporter to the haul road station of their corresponding shovel.

In the truck travel submodel, entities coming after loading (B), or after dumping (F) are first assigned a destination station on the road network based on dispatching. Then using Arena functions next intersection to travel is determined based on shortest path to reach their destinations. After the next intersection is assigned to the entities, failure status of trucks is checked. If the truck status is 'fail' or 'out', trucks are moved to a failure intersection which remain out of main road network, where trucks wait until their status is active when they move back to their original intersection in the road network and start normal travel. If the trucks are found active, trucks are transported to the next intersection with a velocity based on the trucks rimpull curve characteristic and haul road gradient and rolling resistance of the next segment to travel. The load entities appear back into the logic at the haul road stations module where a condition is checked whether the current station is the destination station for the load entity. If the current station is found as the dumping station assigned as destination to the load entity, it is moved to the dumping submodel; or if the current station is found as loading station, it is moved to the loading station; otherwise load entity is assigned its next intersection to travel and transported. Before moving the load entity to the loading submodel, shovel status is checked. If shovel status is found 'fail', the truck is redirected to a different shovel using the truck dispatching logic. The data is collected for every load dumped at dump location. Truck dispatching in simulation is performed by modeling the Dispatch logic given by White and Olson (White & Olson, 1986).

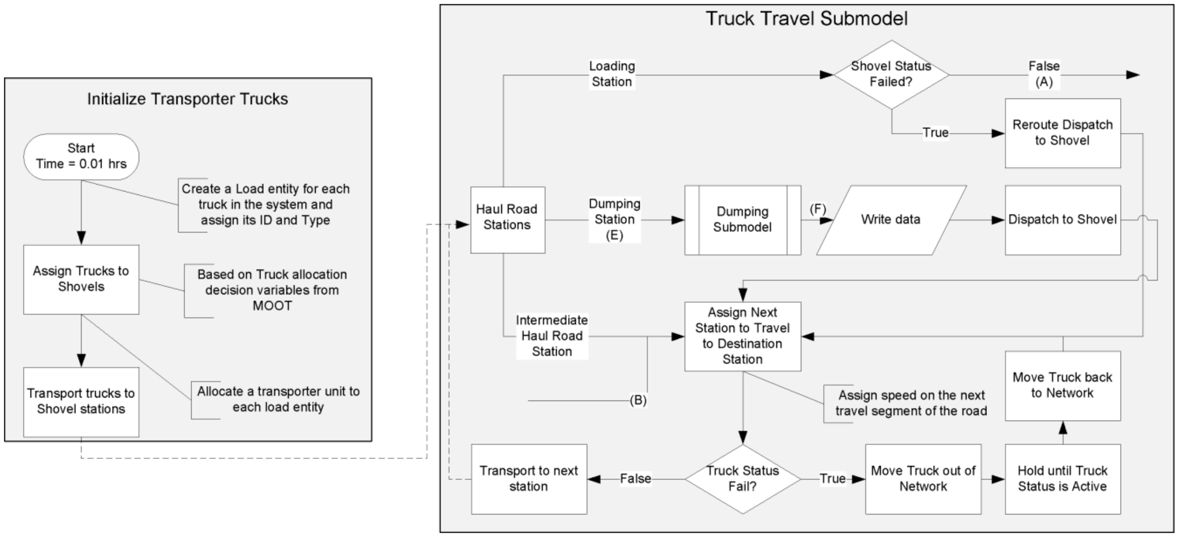

Fig. 9: Flow of the truck travel submodel and the initialization of transporters as trucks

5. Model Implementation

The simulation optimization model presented in this paper is implemented with an iron ore mine case to carry out a detailed verification study. The simulation optimization model is implemented to develop an efficient short term plan for year 11 of the long term schedule. The schedule in year 11 requires mining on four benches 1745, 1730, 1610 and 1595, consisting of 16.42 MT of ore and 39.11 MT of waste. The mining operation is carried out using three waste shovels and two ore shovels with two plant crushers and a waste dump. Both plant crushers operate at an average 2000 ton per hour with hopper capacities of 500 ton each. Plant 1 and plant 2 crusher desire ore with MWT grades of 65% and 75% respectively from the available grade and tonnage distribution in the schedule as given in Fig. 10.

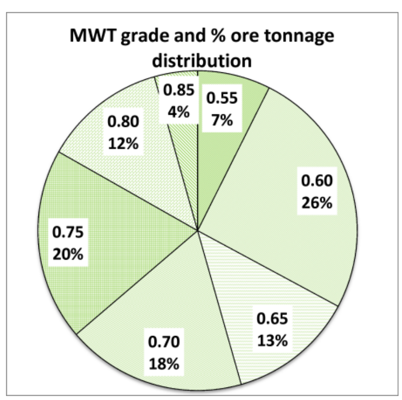

Fig. 10: MWT grade and ore tonnage distribution in schedule

Mine employs two Hit 2500 shovels to work in ore and three Hit 5500EX shovels to mine waste. Mine also employs Cat 785C trucks (truck type 1) with nominal capacity of 140 ton and Cat 793C trucks (truck type 2) with nominal capacity of 240 ton to haul the material.

Mine management want to determine the best short term schedule and the number of trucks to maximize the efficiency of the production operations and meet the strategic schedule. The simulation optimization model is thus implemented on the case study to run over 6 months and 10 replications, to analyze the operations with target ore production of 8.21Mt and waste production of 19.56Mt. The model is not run for the whole year, as such longer time predictions are undesired due to increased uncertainty.

Two cases were analyzed during this implementation, C1: only Cat 785C trucks (truck type 1) in the system, and C2: mixed fleet with Cat 785C trucks locked to ore shovels and Cat 793C trucks (truck type 2) locked to waste shovels. Due to large capacity of Cat 793C trucks, they are locked to large waste shovels, and Cat 785C trucks are locked to ore shovels in case C2.

5.1. Model verification

The results were first analyzed as part of the verification process by comparing the model outputs with the expectations. Key performance indicators (KPIs) of the system were plotted with increasing number of trucks in the system for both cases C1 and C2 to verify the model by comparing the output with the expectations.

Fig. 11 and Fig. 18 show the mean value of observed ore and waste productions with increasing number of trucks in the system over 10 replications for both cases C1 and C2. The total production is expected to increase with increase in number of trucks, till shovels operate at their maximum operating efficiency, which is also observed in both the cases. But Ore productions are not observed to be affecting much in C1. This is because MOOT tries to meet the plant feed rate, which in case of C1 can be achieved by diverting more trucks to work in ore from waste. In case of C2, if number of trucks in ore is not sufficient, due to trucks locked to ore or waste, MOOT cannot divert more hauling capacity to ore shovels. Thus, in C2, ore or waste productions are affected only by changes in number of trucks working with ore or waste shovels specifically. This pattern can also be observed in Fig. 17 and Fig. 23 which shows the individual shovel operating efficiencies in C1 and C2. Ore shovels (S1 and S2) are found to have higher operating efficiencies compared to waste shovels (S3, S4 and S5) in C1, which increases very gradually with increasing number of trucks, whereas operating efficiencies of ore and waste shovels in C2 are found to follow the number of ore and waste trucks in the system. Fig. 23 also shows very less operating efficiency for shovel 5 in the beginning, which happens because of distant location of shovel S5. As number of trucks with waste shovels for scenarios 1 to 4 is very small in C2, MOOT allocates more trucks to closer shovels S3 and S4 to maximize the production.

Average shovel and truck operating efficiencies are shown in Fig. 14 and Fig. 15 for C1 and Fig. 21 and Fig. 22 for C2. The observations show clear and expected relationship between truck and shovel operating efficiencies. As number of trucks in the system increases, hang time of shovels decreases as shown in Fig. 16, increasing shovel operating efficiencies; but at the same time queue times of trucks increases leading to decreased truck operating efficiencies.

Fig. 12, Fig. 13, Fig. 19 and Fig. 20 show the average ton per hour (tph) ore delivered to both plants in both cases. The behavior is found to be following the expectation, but the TPH observed falls short of the target TPH of the plants (2000 tph). The main reason for this is attributed to the operating efficiencies of ore shovels and an average 94% availability of shovels observed. It should be noted here that due to maximum 2000 tph feed capacity to crusher and very limited 500 ton hopper capacity, the delivery rate to hoppers cannot exceed 2000 tph, leading to increased dumping times and queuing times at the plants when delivery rate is higher. But the delivery rate falls short at times shovels are failed, decreasing the tph delivered to plants; and thus average tph observed falls short of target.

The scenarios analyzed have found conformity with the expected behavior of the mining system and desired decision making by MOOT, verifying the model for its correctness and efficiency in capturing the system performance.

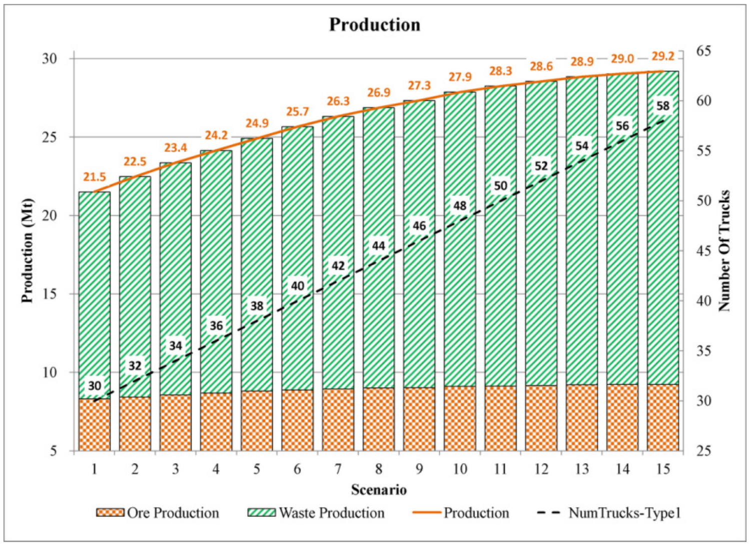

Fig. 11: Ore and waste production observed with increasing number of trucks for case C1

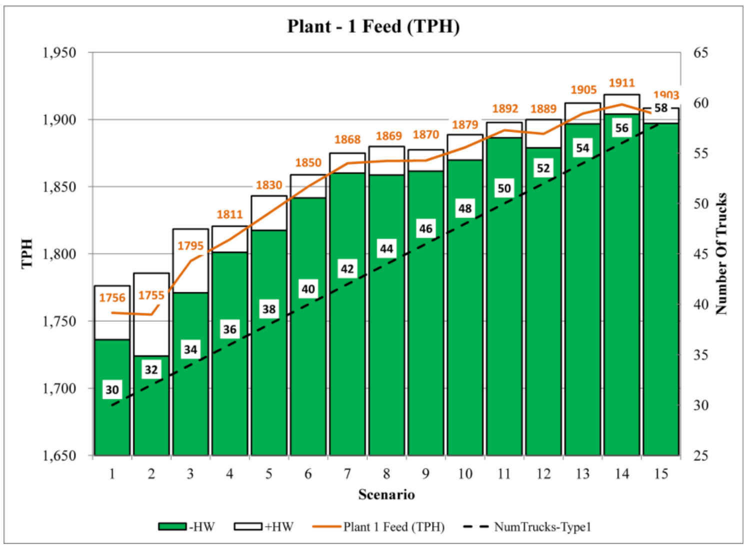

Fig. 12: Ton per hour (TPH) delivered to Plant 1 with increasing number of trucks in case C1

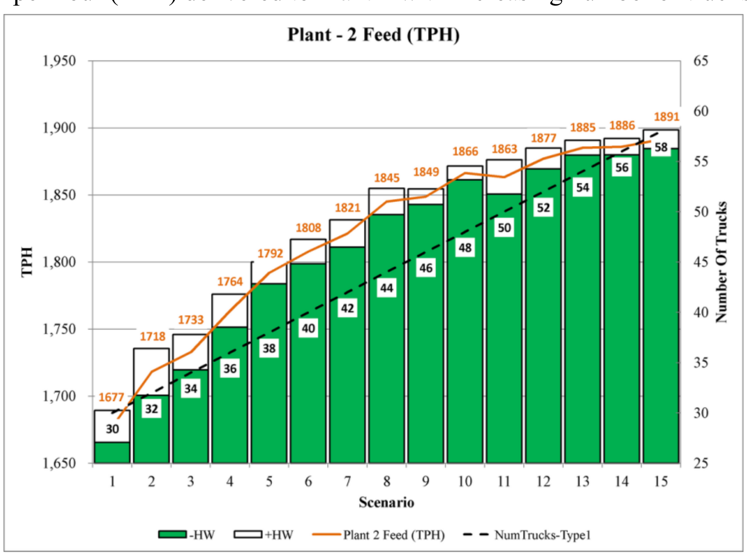

Fig. 13: Ton per hour (TPH) delivered to Plant 2 with increasing number of trucks in case C1

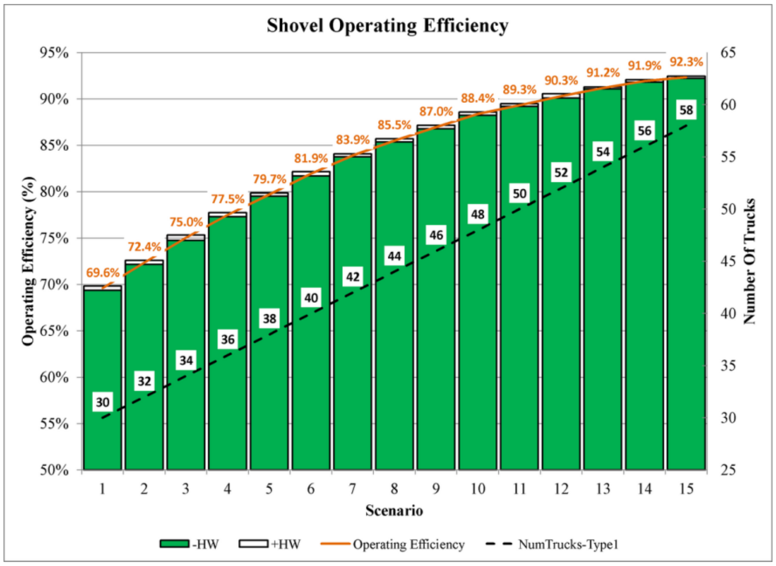

Fig. 14: Shovel operating efficiencies observed with increasing number of trucks in case C1

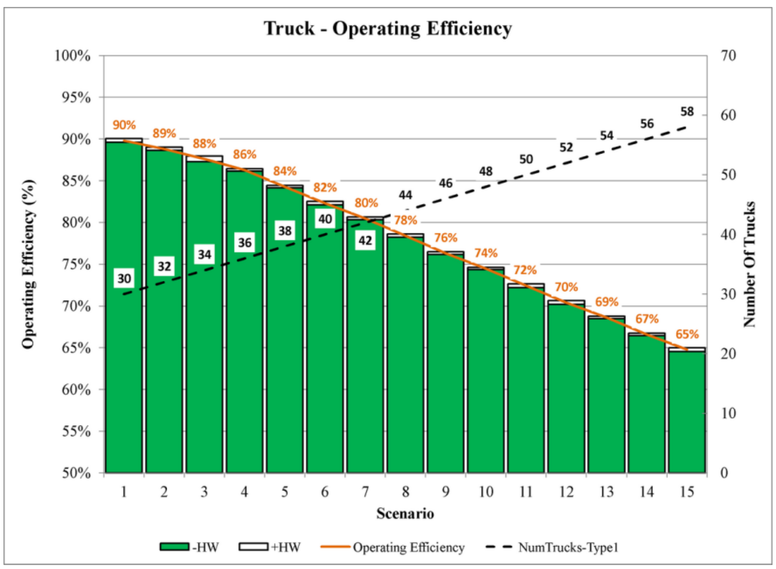

Fig. 15: Truck operating efficiencies observed with increasing number of trucks in case C1

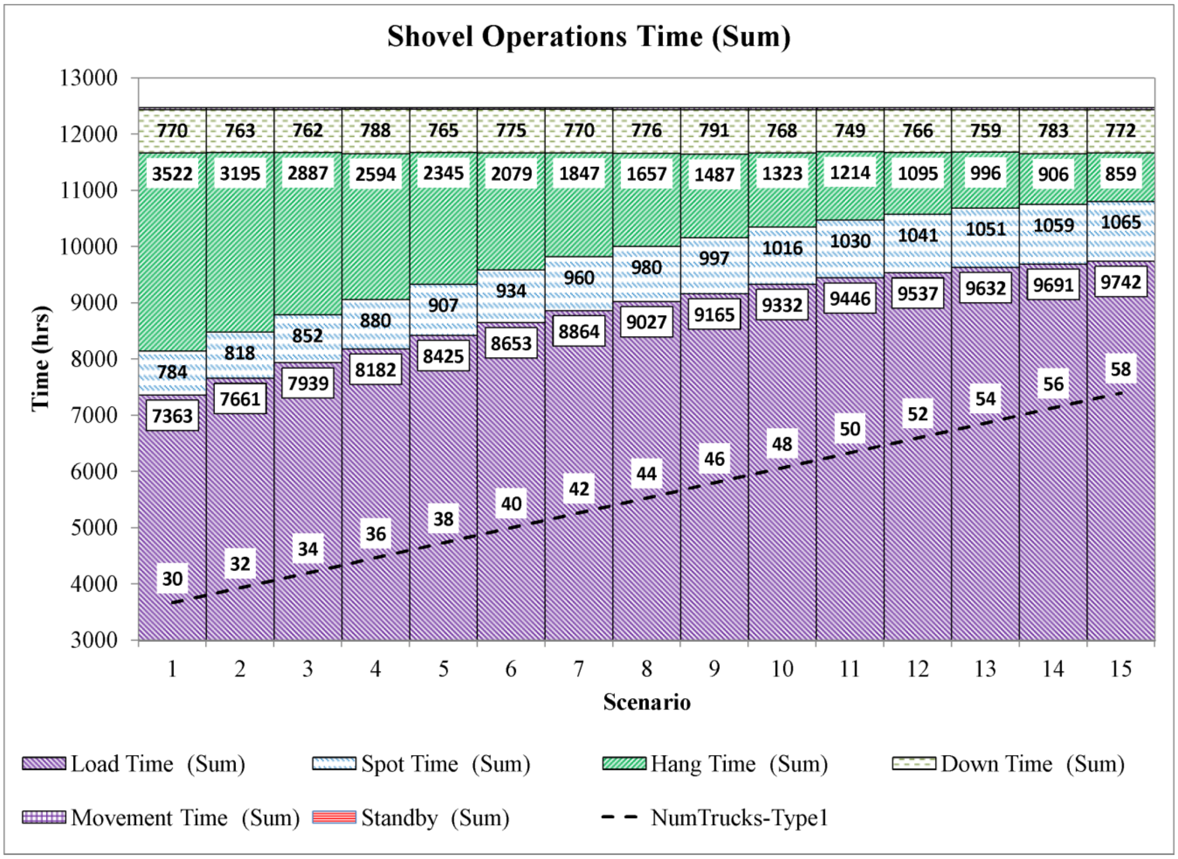

Fig. 16: Distribution of shovel operation times (combined all shovels) with number of trucks in case C1

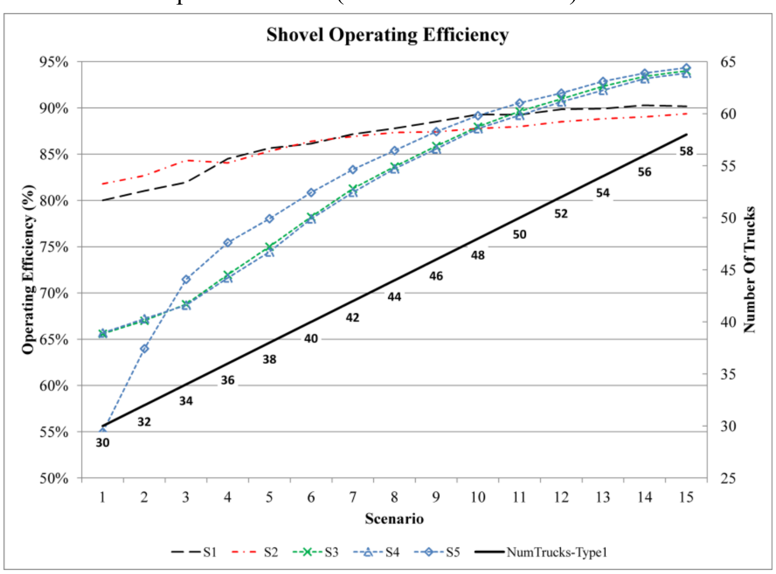

Fig. 17: Individual shovel operating efficiencies observed with number of trucks in case C1

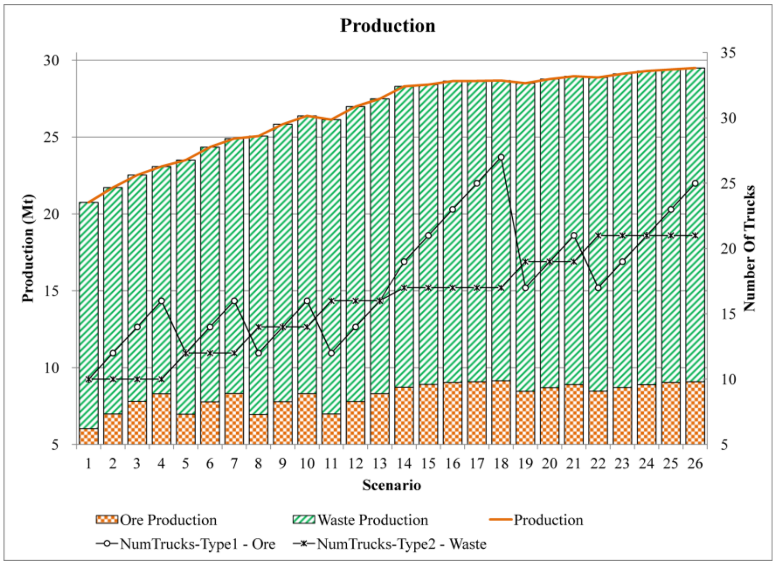

Fig. 18: Ore and waste production observed with increasing number of trucks for case C2

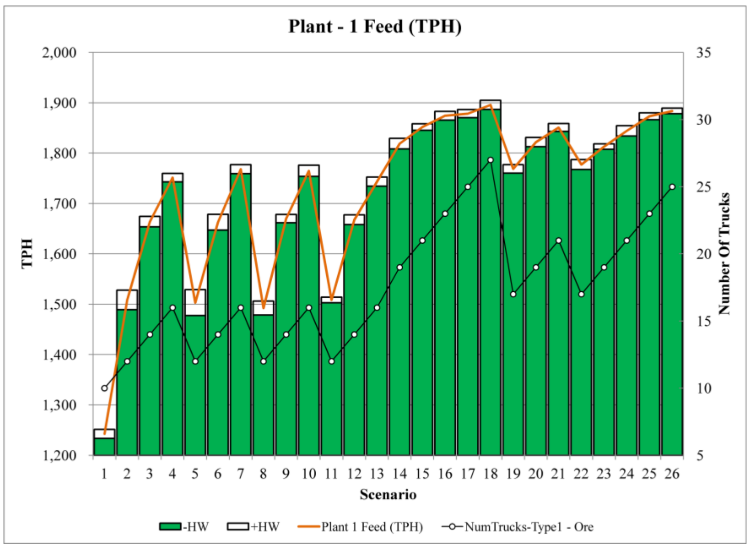

Fig. 19: Ton per hour (TPH) delivered to Plant 1 with increasing number of ore trucks in case C2

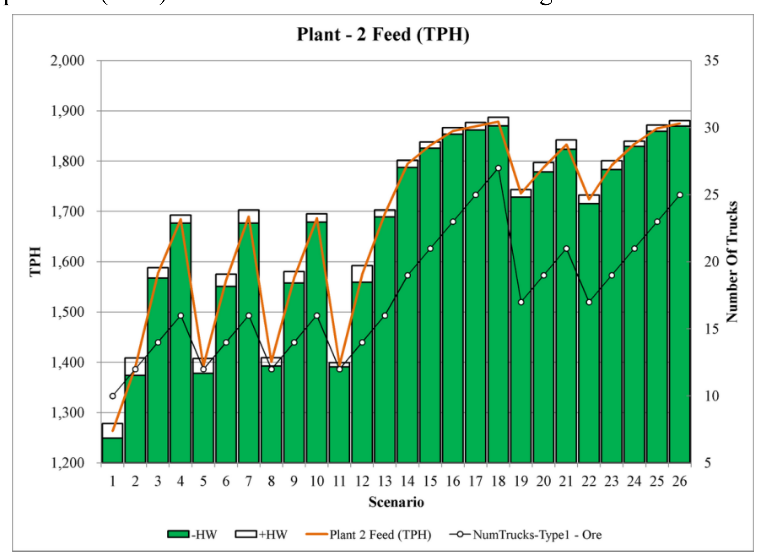

Fig. 20: Ton per hour (TPH) delivered to Plant 2 with increasing number of ore trucks in case C2

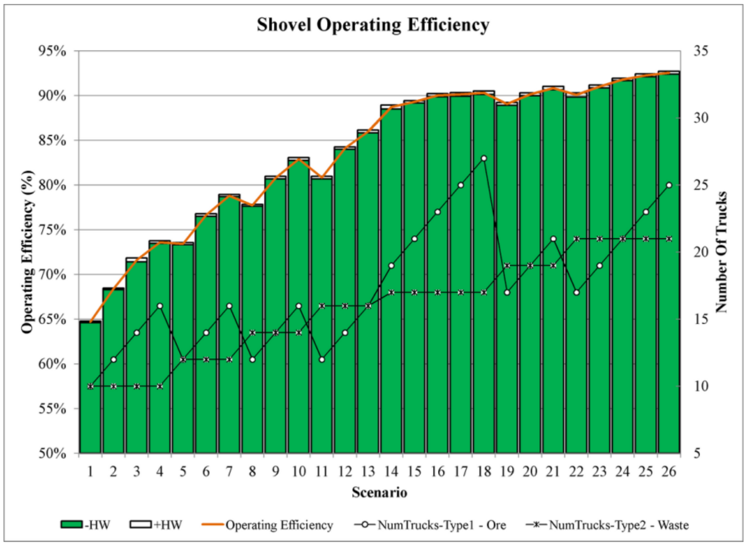

Fig. 21: Shovel operating efficiencies observed with increasing number of trucks in case C2

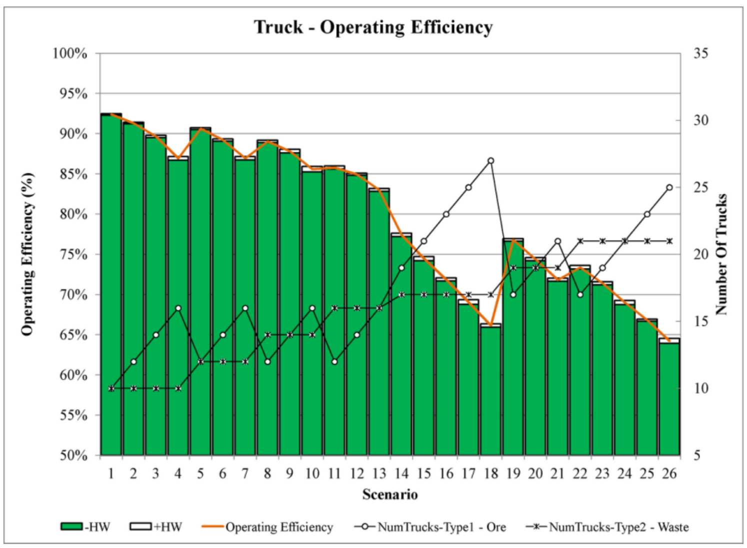

Fig. 22: Truck operating efficiencies observed with increasing number of trucks in case C2

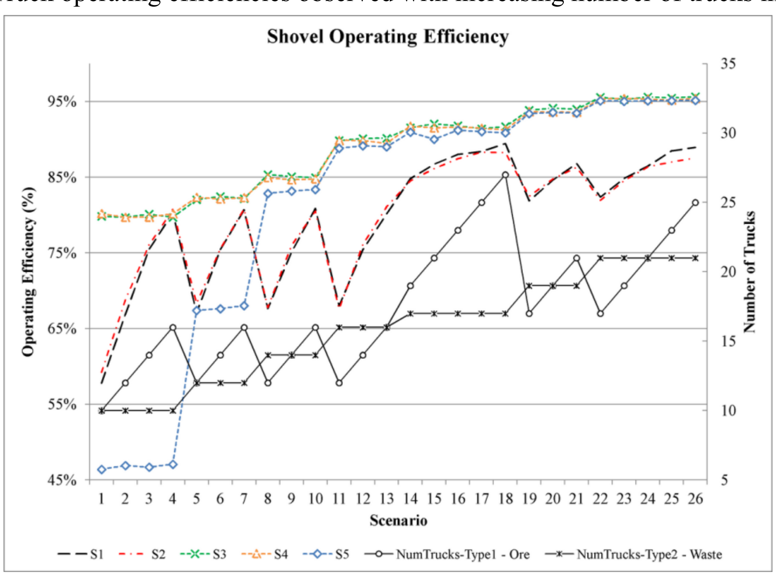

Fig. 23: Individual shovel operating efficiencies observed with number of trucks in case C2

5.2. Scenario selection and analysis

The two cases were analyzed against the target ore and waste productions of 8.21Mt and 19.56Mt respectively, and the operating efficiencies of shovels and trucks to determine the best scenario. In the case C1, scenario 13 was found to be the best scenario which meets the targeted ore and waste productions and provides satisfactory operating efficiencies of 91.2% and 68.63 % respectively. Scenarios 14 and 15 also satisfy the target productions, but are rejected due to further decreasing truck operating efficiencies and very less gain in shovel operating efficiencies.

Similarly in the case C2, scenarios 16, 17 and 19 to 26 satisfy both ore and waste target productions. As shovel operating efficiencies of all the selected scenarios are approximately 90% or above, they were analyzed against truck operating efficiencies. Having a target of above 70% truck efficiency, scenarios 16, 19, 20, 21, 22, and 23 were further screened to be analyzed against TPH delivered to plants where scenario 16 is selected as the best scenario which satisfied plant requirements to the most and found satisfactory for production and operating efficiencies of the equipments for case C2.

Table 2: Comparison of the selected scenarios for case C1 and C2

	C1 – Scenario 13		**C2 – Scenario 16**	
	Mean	Half Width	Mean	Half Width
Ore Production (ton)	9,216,802	25,832	9,036,840	26,665
Waste Production (ton)	19,642,130	73,585	19,605,509	45,807
TPH – Plant 1 (ton/h)	1905	8	1874	9
TPH – Plant 2 (ton/h)	1885	6	1860	6
Shovel Operating Efficiency (%)	91	0.1	90	0.2
Truck Operating Efficiency (%)	69	0.1	72	0.2
Empty Haul Distance (Km)	648,547	1,586	474,020	716
Full Haul Distance (Km)	652,436	1,602	476,068	736

Comparing the selected scenarios from C1 and C2 in Table 2, we can see that best scenario for C1 performs slightly better than best scenario for C2, except truck operating efficiency. But the total haulage distance covered in C2 is much lesser than in C1, which is because of less number of higher capacity trucks used as mixed fleet system in C2. This is an important criterion for an efficient operation, as it affects the life of truck tires and trucks as such, and has a substantial impact on mining cost. Thus best scenario for C2 should be selected. Although due to the mixed fleet system, locking of trucks to shovels becomes necessary that decreases the dispatching efficiency in C2, it is favorable over C1 due to the impact on cost and increased traffic on haul roads with large fleet of smaller trucks in C1.

The selected scenario for C2 is further analyzed for the weekly ore and waste productions (Fig. 24 and Fig. 25), average weekly tph delivered to both plants (Fig. 26 and Fig. 27) and average weekly MWT grade delivered to both the plants (Fig. 28 and Fig. 29). Fig. 24 to Fig. 29 show the efficiency of MOOT in meeting the mine operational objectives of maximizing the production and meeting the quantity and quality requirements of the plants. The average weekly grades delivered to plant 1 (Fig. 28) and plant 2 (Fig. 29) show the efficient grade blending obtained compared to the available grades in schedule as shown in Fig. 10. The grade blending in this approach is not obtained merely by truck dispatching, but also by optimally allocating the shovels to the best faces so that blending can be achieved by truck dispatching. As decisions made by MOOT takes into account shovel allocations in further periods as well, the decisions are far sighted as well so that operations are efficient throughout the production period.

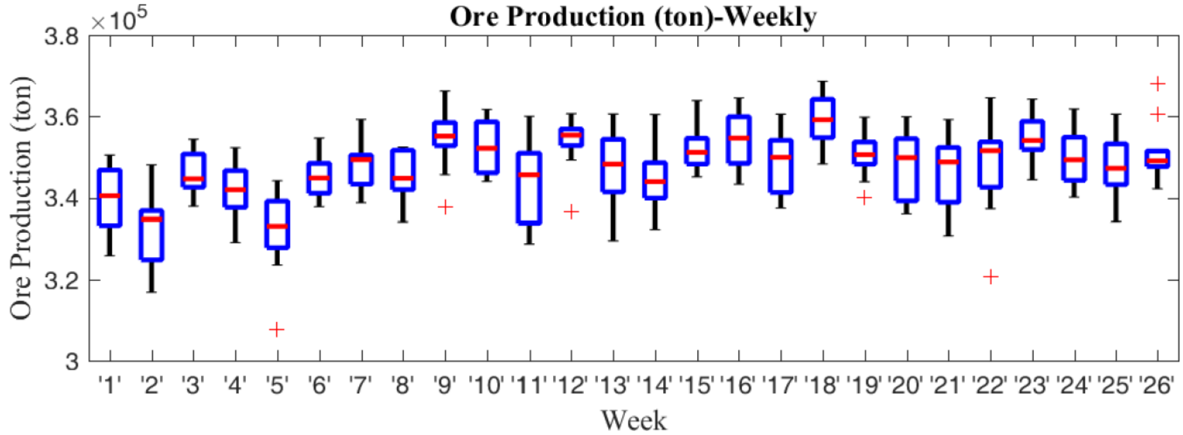

Fig. 24: Weekly ore production for the selected scenario in C2

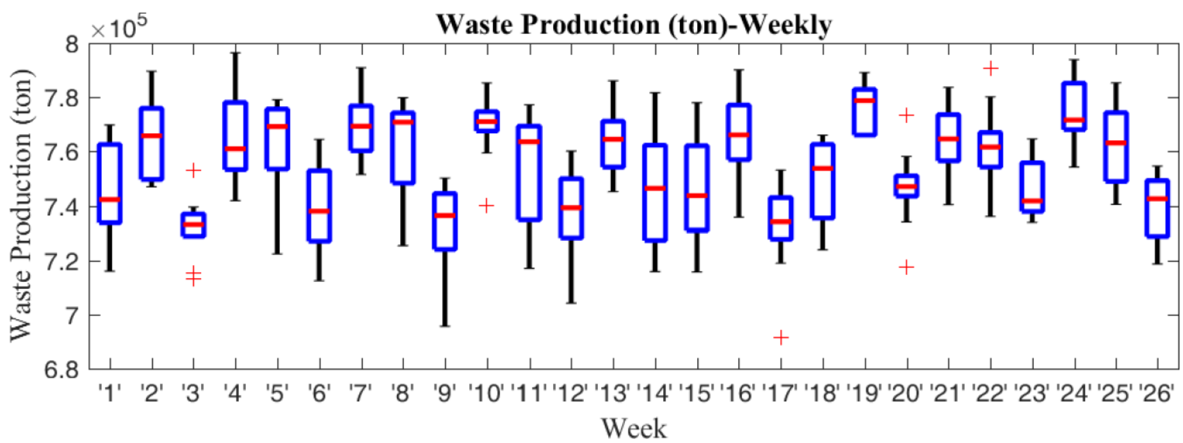

Fig. 25: Weekly waste production for the selected scenario in C2

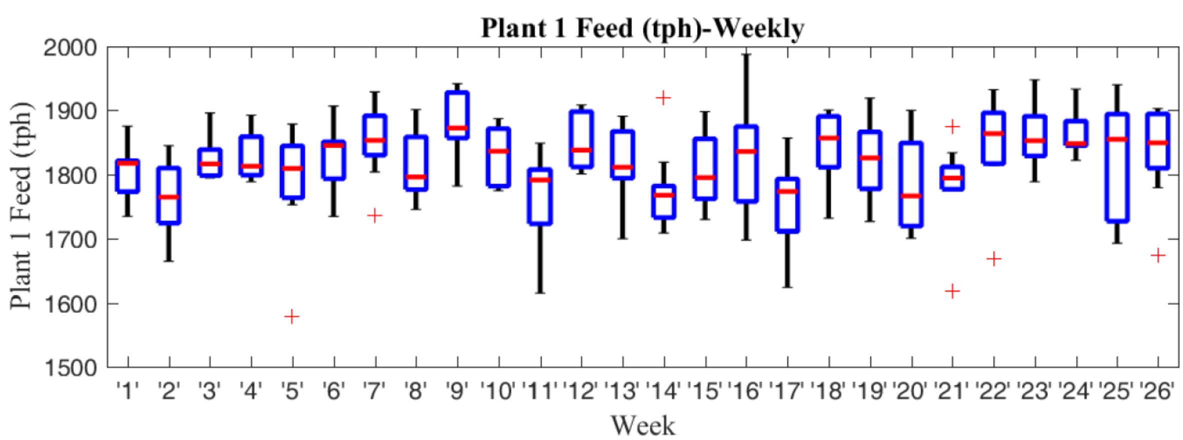

Fig. 26: Weekly average ton per hour delivered to plant 1 for the selected scenario in C2

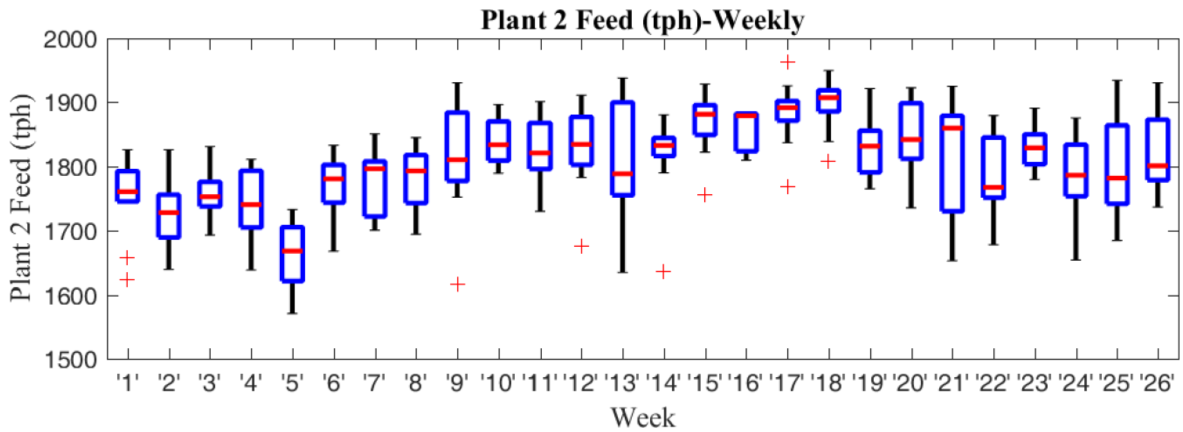

Fig. 27: Weekly average ton per hour delivered to plant 2 for the selected scenario in C2

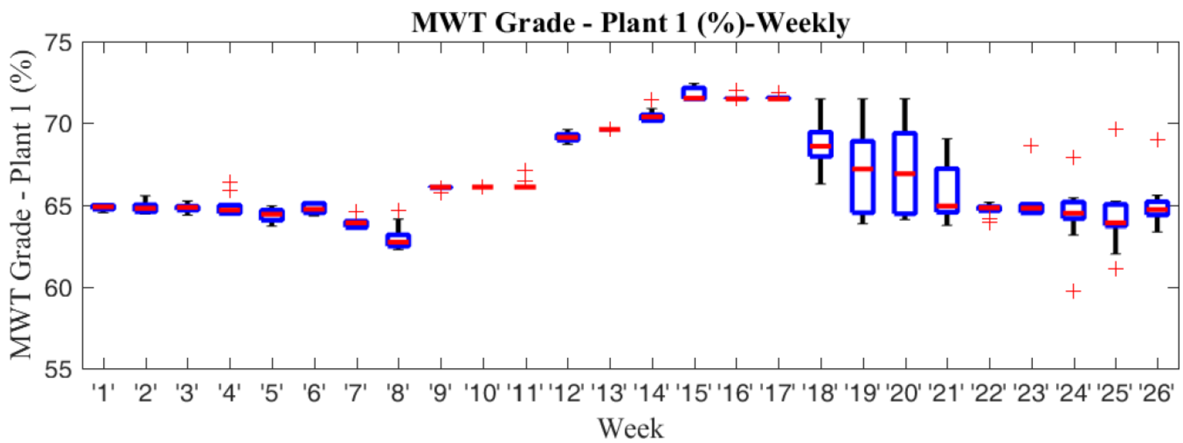

Fig. 28: Weekly average MWT grade delivered to plant 1 for the selected scenario in C2

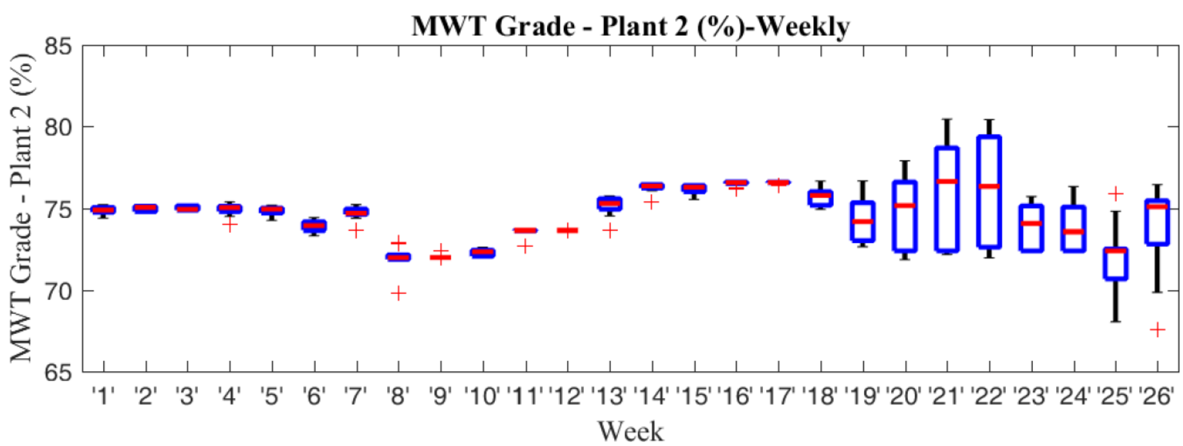

Fig. 29: Weekly average MWT grade delivered to plant 2 for the selected scenario in C2

Various other scenarios can be run at this stage by changing other system characteristics, such as mine haul road design, different weight to blending objectives for both plants if desired and increased hopper capacities etc. to optimize the mine operations performance based on desired objectives. The shovels assignments for the best replication result in the selected scenario can be used to create the short term schedule to be implemented into actual mine operations.

6. Conclusions and recommendations

This paper presented a novel approach towards short term mine production planning and optimization. The detailed verification studies of the simulation optimization model presented show its capability in modeling the mine operations and providing efficient mine operational decisions using MOOT. Also, the flexibilities provided in modeling the system using VBA and Matlab tools make the model easily implementable and reusable over time. The model in its current form is capable of efficient short term planning by analyzing the impact of different haul road designs, haul road conditions, traffic congestions, different dispatching strategies and varying plant requirements on mine operations.

The very unique characteristic addition of the proposed simulation optimization approach in the short term mine planning process is the ability to incorporate minor details of mine operations in the planning process and help in proactive decision making. Including further characteristics into the simulation model, the approach is capable of providing realistic and practical short term schedule by capturing:

- Effect of haul road conditions on tire cost expenditures of trucks
- Effect of accidents on truck speeds and in-turn on production
- Effect of different dispatching algorithms or truck locking strategies
- Detailed cost estimations in production operations

7. References

[1] Ataeepour, N., & Baafi, E. Y. (1999). ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. *International Journal of Surface Mining, Reclamation and Environment, 13*(3), 125-130.

[2] Awuah-Offei, K., Temeng, V. A., & Al-Hassan, S. (2003). Predicting equipment requirements using SIMAN simulation a case study. *Transactions of the Institution of Mining and Metallurgy Section A-Mining Technology, 112*(3), A180-A184.

[3] Bjørndal, T., Herrero, I., Newman, A., Romero, C., & Weintraub, A. (2012). Operations research in the natural resource industry. *International Transactions in Operational Research, 19*(1-2), 39-62.

[4] Eivazy, H., & Askari-Nasab, H. (2012). A mixed integer linear programming model for short-term open pit mine production scheduling. *Mining Technology, 121*(2), 97-108.

[5] Fioroni, M. M., Franzese, L. A. G., Bianchi, T. J., Ezawa, L., Pinto, L. R., & de Miranda, G. (2008). *Concurrent simulation and optimization models for mining planning*. Paper presented at the WSC 2008.

[6] Gholamnejad, J. (2008). A zero-one integer programming model for open pit mining sequences. *Journal of the Southern African Institute of Mining and Metallurgy, 108*, 759-762.

[7] Grodzevich, Oleg, & Romanko, Oleksandr. (2006). *Normalization and Other Topics in Multi-Objective Optimization*. Paper presented at the Fields-MITACS Industrial Problems Workshop.

[8] Gurgur, C., Dagdelen, K., & Artittong, S. (2011). Optimization of a real-time multi-period truck dispatching system in mining operations. *International Journal of Applied Decision Sciences, 4*(1), 57-79.

[9] Henderson, R., & Turek, C. (2013). Mine planning best practice at Kinross Gold. [doi: 10.1179/1743286313Y.0000000041]. *Mining Technology, 122*(2), 86-93.

[10] Jaoua, A., Riopel, D., & Gamache, M. (2009). A framework for realistic microscopic modelling of surface mining transportation systems. [doi: 10.1080/17480930802351479]. *International Journal of Mining, Reclamation and Environment, 23*(1), 51-75.

[11] Jaoua, Amel, Gamache, Michel, & Riopel, Diane. (2012). Specification of an intelligent simulation-based real time control architecture: Application to truck control system. *Computers in Industry, 63*(9), 882-894.

[12] Kolonja, B., & Mutmansky, J. M. (1994). Analysis of truck dispatching strategies for surface mining operations using SIMAN. *Transactions - Society for Mining Metallurgy And Exploration Incorporated, 296*, 1845-1851.

[13] Kumral, M., & Dowd, P. A. (2002). Short-term mine production scheduling for industrial minerals using multi-objective simulated annealing, *in Proceedings of the 30th Application of Computer in Mineral Industry Symposium (APCOM '02)* (pp. 731-742). Fairbanks, Alaska, USA.

[14] L'Heureux, G., Gamache, M., & Soumis, F. (2013). Mixed integer programming model for short term planning in open-pit mines. [doi: 10.1179/1743286313Y.0000000037]. *Mining Technology, 122*(2), 101-109.

[15] Malhotra, Yash P., & List, Sarah J. (1989). Short term mine planning at Syncrude. [doi: 10.1080/09208118908944248]. *International Journal of Surface Mining, Reclamation and Environment, 3*(1), 11-20.

[16] Rist, K. (1961). *The solution of a transportation problem by use of a Monte Carlo Technique*. Paper presented at the APCOM 1.

[17] Rockwell Automation Inc. *Arena*.

[18] Sturgul, J. R. (1999). Discrete mine system simulation in the United States. *International Journal of Surface Mining, Reclamation and Environment, 13*(2), 37-42.

[19] The MathWorks Inc. *Matlab-R2015b*. Natick, Massachusetts, United States.

[20] Upadhyay, S. P., Suglo, R. S., Lin, Z., Sundararajan, S., & Szymanski, J. (2013). Simulation analysis model and equipment selection in continuous surface mining systems. *CIM Journal, 4*(2), 87-94.

[21] White, J.W., & Olson, J.P. (1986). Computer-based dispatching in mines with concurrent operating objectives. *Mining Engineering, 38*(11), 1045-1053.

[22] Yuriy, Greg, & Vayenas, Nick. (2008). Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms. *International Journal of Mining, Reclamation and Environment, 22*(1), 70-83.

8. Appendix

8.1. Indices

Table 3: Indices for variables, parameters and sets

s	Index for set of shovels (s = 1, … $\hat{S}$)
f	Index for set of faces (f = 1, … $\hat{F}$)
t	Index for set of truck types trucks (t = 1, … $\hat{T}$)

k	Index for set of material types (k = 1, … $\hat{K}$)
d	Index for set of destinations (processing plants, stockpiles, waste dumps)
d^c	Index for set of crushers/processing plants (d^c = 1, … $\hat{P}$)
d^o	Index for ore destinations (processing plants and stockpiles)
d^w	Index for waste dumps (d^w = 1, … $\hat{W}$)
p	Index for periods (p=1,…P)

8.2. Parameters

Table 4: Parameters of systems considered

N_t^T	Number of trucks of type t
H_t	Tonnage capacity of truck type t
J	Flexibility in tonnage produced, to allow fractional overloading of trucks (tonne)
V_t	Average speed of truck type t when empty (Km/hr)
$\bar{V}_t$	Average speed of truck type t when loaded (Km/hr)
C_t	Cost of empty truck movement ($/Km)
$\bar{C}_t$	Cost of loaded truck movement ($/Km)
$M_{t,s}^T$	Binary match parameter, if truck type t can be assigned to shovel s
X_s	Shovel bucket capacity (tonne)
X_s^+	Maximum possible shovel production in decision time frame 'T' (tonne)
X_s^-	Minimum shovel production desired in decision time frame 'T' (tonne)
L_s	Shovel loading cycle time (seconds)
U_s^+	Maximum desired shovel utilization (%)
U_s^-	Minimum desired shovel utilization (%)
A_s	Cost of shovel movement ($/meter)
S_s	Movement speed of shovel (meter/minute)
α_t^T	Truck availability (fraction)
α_s^S	Shovel availability (fraction)
Fi_s	Face where shovel is initially located (start of the shift)
D_f^{FE}	Distance to exit from face f

D_d^{ED}	Distance to destination d from the pit exit
Z_{d^c}	Maximum capacity of the crushers/processing plants (tonne/hr)
$\Lambda_{d^c}^{+}$	Maximum positive deviation in tonnage accepted at crushers/processing plants (tonne/hr)
$\Lambda_{d^c}^{-}$	Maximum negative deviation in tonnage accepted at crushers/processing plants (tonne/hr)
G_{k,d^o}	Desired grade of material types at the ore destinations
G_{k,d^o}^{-}	Lower limit on grade of material type k at ore destinations
G_{k,d^o}^{+}	Upper limit on grade of material type k at ore destinations
F_f^x, F_f^y, F_f^z	x, y, z coordinates of the faces available for shovel assignment (meters)
N_f^F	Number of precedence faces required to be mined before mining face *f*
$\overline{G}_{f,k}$	Grade of material type k at face f
O_f	Tonnage available at face f at the beginning of optimization (tonne)
$O_{\min}$	Minimum material at face below which a face is considered mined
Q_f	1 if material at face is ore, 0 if it is waste (binary parameter)
T	Decision time frame (hr)
Π^{-}	Lower limit on desired stripping ratio
Π^{+}	Upper limit on desired stripping ratio
Γ_{f^1,f^2}^{F}	Distance between available faces (meters), calculated as linear distance between faces on the same bench, and following the haul road and ramps between faces on different benches.
$\Gamma_{f,d}^{D}$	Distance of destinations from faces, based on the haulage profile in short-term schedule (meters)
$\tau_{s,f}$	Movement time of shovel s from initial face to face f (minutes)
$\overline{T}_{t,f,d}$	Cycle time of truck type t from face f to destination d (minutes)
ϕ_s	0 or 1 binary variable if shovel *s* is working or failed
M_s^{ore}	Parameter, if shovel *s* is locked to an ore face 0, waste face 1 otherwise 2
W_i	Normalized weights of individual goals (i = 1, 2, 3, 4) based on priority
ε	A very small decimal value to formulate strict in-equality (depending on constraint)
BM	A very large number (depending on constraint)

Block-cave Operations Optimization using Linear Programming with Absolute Values

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Abstract

For any block cave mining operation it is important to maintain a uniform extraction profile for the life of the mine. A uniform extraction profile reduces horizontal movements of the material between drawpoints in the same neighborhood and as a result minimizes the dilution. Achieving such an extraction profile while satisfying the constraints could be a challenge for the block caving operations. This research uses mathematical programming as a strong tool to model the operation in block cave mining with the objective function in which minimizes the deviation of extraction from drawpoints. The problem was first formulated as a quadratic programming model then the problem was converted to a linear programming with absolute values. Technical and operational constraints such as mining capacity, average grade for production, continuous mining, drawpoint's life, draw control and number of active drawpoints are considered for the operations. Testing both the quadratic and the linear model with absolute values for a real case mining project shows that the linear model with absolute values is easier and faster to solve.

1. Introduction

In this research, production scheduling in block-cave mining is optimized with respect to the objective function and the constraints using mathematical programming. First the background and a brief literature of this research is reviewed, then the model and related parameters are discussed. A case study is presented to verify the model and the results are presented. The problem is modeled in MATLAB and solved using CPLEX.

2. Background

A mining project usually deals with high rates of material movement, capital and operation costs, and in most cases, high rates of returns. Production scheduling is one of the sensitive decision making processes for this type of operations in which there is a huge difference between an operations with optimal or non-optimal production schedule. An optimum production schedule can significantly increase the profitability of the project while a project could be even failed because of a poor schedule. Since the surface mining has been going deeper, the stripping ratios have significantly increased. Bigger open-pits will result in more environmental concerns and more expensive closure plans. In such a situation, underground mining with less waste movement and environmental issues can be more reasonable. Among underground mining methods, block cave mining with high rates of production and low operation cost is a good alternative for open-pit mining. In block cave mining, after determining the extraction level, an undercut is carried on at the bottom of the orebody so that the rock starts breaking down, then the fragmented material can be extracted by the constructed drawpoints. A schematic view of block cave mining is shown in Fig.1.

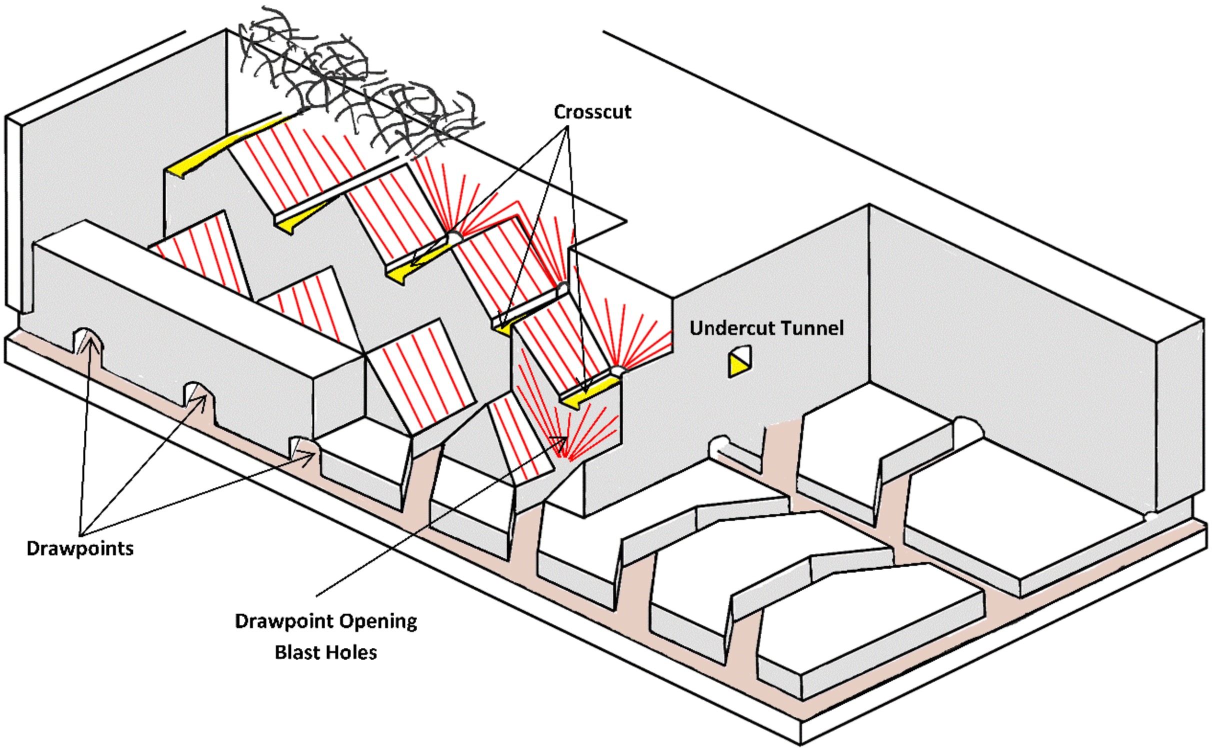

Fig.1. Block cave mining

3. Literature review

There is a significant amount of research for application of mathematical programming in production scheduling for mining projects. Researchers have used linear programming (LP), mixed–integer programming (MIP, MILP), and quadratic programming (QP). The models have mostly been proposed for open-pit operations (Newman, Rubio, Caro, Weintraub, & Eurek, 2010). Some researchers have been looking at production scheduling optimization for block cave mining such as; Song (1989), Chanda (1990), Guest, Van Hout, and Von Johannides (2000), Rubio (2002), Rahal, Smith, Van Hout, and Von Johannides (2003), Diering (2000), Rubio and Diering (2004), Rahal (2008), Pourrahimian, Askari-Nasab, and Tannant (2012), Pourrahimian, Askari-Nasab, and Tannant (2013), Khodayari and Pourrahimian (2014). A detailed literature review of production scheduling in block-cave mining can be found in (Khodayari & Pourrahimian, 2015).

4. Modeling

The model's aim is to optimize the long-term production schedule for a block-cave mine so that the deviation of the extracted tonnages (*extton*) of drawpoints from the defined initial tonnages (*expton*) is minimized with respect to the technical and operational constraints. The indices, variables, and parameters which are used in the models are defined as below:

4.1. Notation

- Indices

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

$n \in \{1,...,N\}$	Index for individual drawpoints
g_n	Average copper grade of draw column *n* associated with drawpoint *n*
ton_n	Ore tonnage of draw column *n* associated with drawpoint *n*

- Variables

$ext\,\mathrm{ton}_n^t$	The tonnage of extraction for drawpoint n at period *t* based on the solution of the production scheduling problem (the optimum tonnages that we are looking for, considering the problem's constraints)
Z_n^t	The new set of continuous variables which connects the quadratic model to linear
$X_n^t \in [0,1]$	Continuous decision variable that represents the portion of draw column *n* which is extracted in period *t*
$(Y1)_n^t \in \{0,1\}$	First set of binary variables which determines whether drawpoint *n* in period *t* is active [$(Y1)_n^t = 1$] or not [$(Y1)_n^t = 0$]
$(Y2)_n^t \in \{0,1\}$	Second set of binary variables which determines whether drawpoint *n* till period *t* (periods 1, 2,..,t) has started its extraction [$(Y2)_n^t = 1$] or not [$(Y2)_n^t = 0$]

- Parameters

$\exp ton_n^t$	The expected tonnage of extraction for drawpoint *n* at period *t* which is defined based on the production goals
$DP_n^t \in [0,1]$	Depletion Percentage, the portion of draw column *n* which has been extracted till period *t*
$M_{\min}$	Minimum mining capacity based on the capacity of mining equipment
$M_{\max}$	Maximum mining capacity based on the capacity of mining equipment
$G_{\min}$	Minimum production grade
$G_{\max}$	Maximum production grade
$ActMin$	Minimum number of active drawpoints in each period
$ActMax$	Maximum number of active drawpoints in each period
M	An arbitrary big number
$MaxDrawLife$	Maximum life of drawpoints

4.2. Mixed integer quadratic programming model

This model is defined based on a mixed integer quadratic objective function and the linear constraints. The objective function is as following:

$$Minimize \ \sum_{t=1}^{T}\sum_{n=1}^{N}(ext\,\text{ton}_n^t - \text{exp}\,ton_n^t)^2 \quad (1)$$

$$= \sum_{t=1}^{T}\sum_{n=1}^{N}(ext\,\text{ton}_n^t)^2 - (2\times ext\,\text{ton}_n^t)\times \text{expton}_n^t$$

$$= \sum_{t=1}^{T}\sum_{n=1}^{N}(ton_n \times X_n^t)^2 - (2\times \text{expton}_n^t \times ton_n)\times X_n^t$$

This quadratic formulation can be modeled based on the following basic problem:

$$Minimize \ 0.5\times \text{X}'\times \text{H}\times \text{X}+\text{f}\times \text{X} \quad (2)$$

Where *X* is the matrix of variables, *H* is the coefficient matrix of the quadratic part, and *f* is the coefficient matrix for the linear part of the formulation. There are both continuous and binary variables, so the model is called mixed integer quadratic programming (MIQP). This formulation will be converted to a mixed integer linear programming with absolute values at the end of this section.

4.3. Constraints

In any real mining operation, many constraints can control the operations and force the management team to make decisions based on those conditions. This research has been trying to consider the key constraints which limit the operations and the production plan.

Binary variables and constraints

To define some of the constraints, it was needed to add several binary constraints in order to make sure that the binary variables work and can be properly used for the other constraints. Two sets of binary variables are used to be able to define the related constraints in the model:

- Set 1: $(Y1)_n^t \in \{0,1\}, \begin{Bmatrix} n \in N \\ t \in T \end{Bmatrix}$

This set contains N×T variables, which means for each drawpoint there is one variable per each period. Variables (N×T) +1 to (2×N×T) in the model are allocated to this set. This set determines whether drawpoint *n* is active in period *t* or not; if any extraction from drawpoint *n* at period *t* occurs then the drawpoint is active (x>0) and $(Y1)_n^t = 1$. If there is no any extraction (x=0) then it is inactive and $(Y1)_n^t = 0$. The mathematical formulation for this set of constraint includes two parts of equations:

$$\forall t \in T \ \& \ n \in N \rightarrow \quad (Y1)_n^t - M.x_n^t \le 0 \quad (3)$$

$$\forall t \in T \ \& \ n \in N \rightarrow \quad x_n^t - (Y1)_n^t \le 0 \quad (4)$$

- Set 2: $(Y2)_n^t \in \{0,1\}, \begin{Bmatrix} n \in N \\ t \in T \end{Bmatrix}$

This set also contains N×T variables. Variables (2×N×T) +1 to 3×N×T in the model are allocated to this set. This set determines whether the depletion percentage of drawpoint *n* in period t is 0 or not. Depletion percentage (DP) is the summation of the x values for drawpoint *n* from period *1* to period *t* based on the draw rate curve.

$$\forall n \in N \rightarrow \quad DP_n^t = \sum_{t=1}^{t} x_n^t \quad (5)$$

Two equations are defined for this set:

$$\forall t \in T \ \& \ n \in N \rightarrow \quad DP_n^t - (Y2)_n^t \le 0 \tag{6}$$

$$\forall t \in T \ \& \ n \in N \rightarrow \quad (Y2)_n^t - M.DP_n^t \le 0 \tag{7}$$

Mining capacity

Based on the mining space, the equipment and the required feed for the processing plant, we are limited to a certain amount of extraction for the mine in different periods of production during the life of the mine:

$$\forall t \in T \rightarrow \quad M_{\min} \le \sum_{n=1}^{N} ton_n \times X_n^t \le M_{\max} \tag{8}$$

Average mining grade

The processing plant is defined based on the quantity and quality of the material which is sent by the mine, the mining capacity (as it was mentioned above) takes care of the quantity and the constraint for average grade of production is defined to guarantee the quality which is the production grade:

$$\forall t \in T \rightarrow \quad G_{\min} \times (\sum_{n=1}^{N} ton_n \times X_n^t) \le \sum_{n=1}^{N} g_n \times ton_n \times X_n^t \tag{9}$$

$$\forall t \in T \rightarrow \quad \sum_{n=1}^{N} g_n \times ton_n \times X_n^t \le G_{\max} \times (\sum_{n=1}^{N} ton_n \times X_n^t) \tag{10}$$

Reserve

This constraint makes sure that the mine reserve which is calculated based on the best height of draw (BHOD) is extracted during the life of the mine:

$$\forall n \in N \rightarrow \quad \sum_{t=1}^{T} X_n^t = 1 \tag{11}$$

Active drawpoints

This constraint limits the number of the active drawpoints in different periods during the life of the mine. This will facilitate the decision making process for the management team.

$$\forall t \in T \rightarrow \quad ActMin \le \sum_{n=1}^{N} (Y1)_n^t \le ActMax \tag{12}$$

Mining direction

In block-cave mining, the drawpoints are designed in a layout; the extraction from drawpoints is started from one location and then expands continuously through the layout to a point where the whole ore body is extracted. Because of the economic value of the material and the geotechnical parameters, it is important where to start and which direction to expand. The mining direction constraint, finds the optimum direction based on the economic values of the draw columns, and then the best direction is manually defined. Fig. 2 shows an example of the mining direction for a block-cave layout (the mining starts from the South-East and then expands toward the North-West of the deposit).

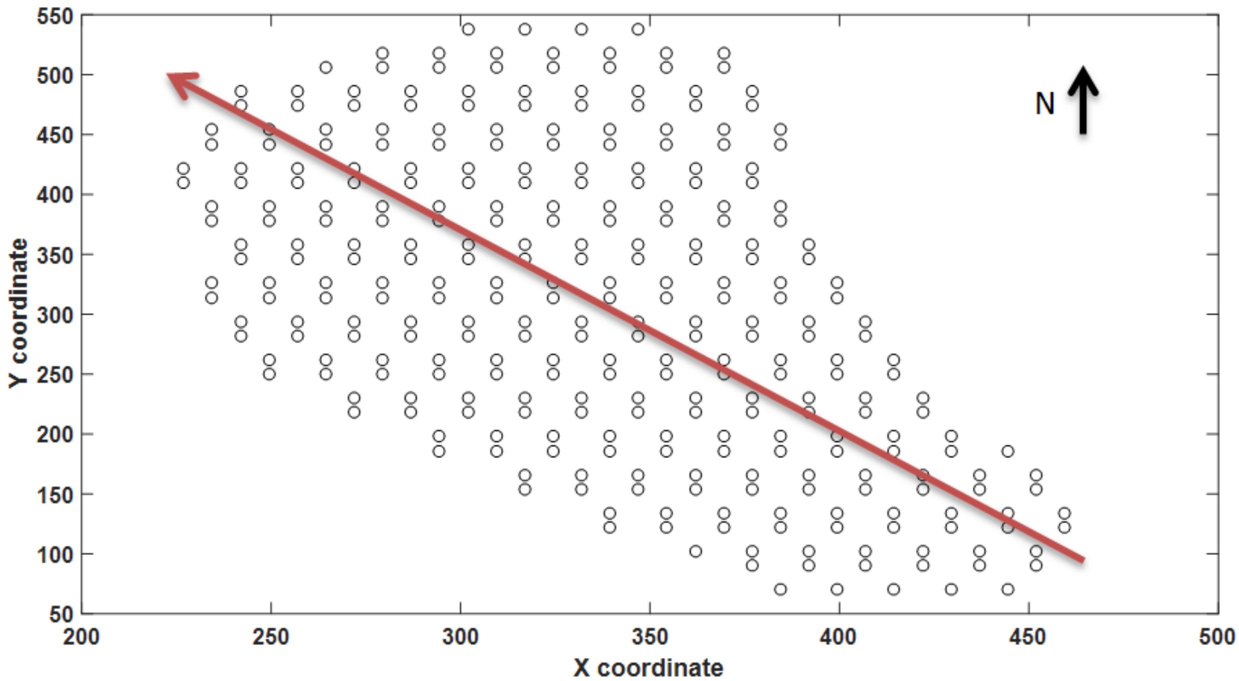

Fig. 2. Mining direction for a block-cave layout

For doing that; first the drawpoints which are located in the neighborhood of each drawpoint are found using a defined radius, the combination of a drawpoint and its neighbors is called production block, then the economic values of production blocks are calculated and compared, the production block with maximum economic value is where the extraction should start, and the expansion follows the direction toward the production blocks with lower economic values. More details about mining direction determination can be found in one of the author's paper (Khodayari & Pourrahimian, 2014).

Mining precedence

When the direction is determined, the precedence can be defined based on the direction so that for each drawpoint the extraction will be started if the extraction of its neighbors which are located ahead has already been started. The following equation defines this constraint:

$$\forall n \in N \ \& \ t \in T \rightarrow \qquad S * (Y2)_n^t \leq \sum_{m=1}^{S} (Y2)_m^t \tag{13}$$

Where *S* is the number of drawpoints in the neighborhood of drawpoint *n* which are ahead (based on the defined direction) and *Y2* is the second set of binary variables.

Continuous mining

When extraction from a drawpoint is started, it should be continued till end of its life. This constraint limits the model to maintain the continuity of operations for drawpoints during the life of the mine:

$$\forall n \in N \& t \in T \rightarrow \qquad (Y1)_n^t + DP_n^{t-1} \geq (Y1)_n^{t-1} \tag{14}$$

Draw control

The tonnage of material which is going to be extracted from each of drawpoints in each period (or draw rate) during the life of the mine is controlled by this constraint. This will also control the height of extraction from each of draw columns.

$$\forall n \in N \,\&\, t \in T \rightarrow \qquad ton_n \times X_n^t \geq \min(ton) \times (Y1)_n^t \tag{15}$$

Where *min(ton)* is the minimum tonnage of draw columns based on the best height of draw (BHOD).

Draw life

For an optimum production schedule, the life of each drawpoint is important, in other words, a drawpoint produces for a certain time during the life of the mine.

$$\forall n \in N \rightarrow \qquad \sum_{t=1}^{T} (Y1)_n^t \leq MaxDrawLife \tag{16}$$

4.4. Conversion to mixed integer linear model with absolute values

It is not easy to solve the MIQP model and solving process is usually time consuming; it takes days to get answers with the MIP gap close to 5%. Even powerful computers can easily go to the situation which the RAM is not enough for solving the problem. The proposed quadratic problem can be converted to a linear programming problem with the absolute values. The conversion would be as following:

$$Minimize \ \sum_{t=1}^{T}\sum_{n=1}^{N} (ext\,\mathrm{ton}_n^t - \exp ton_n^t)^2 \rightarrow Minimize \sum_{t=1}^{T}\sum_{n=1}^{N} \left| ext\,\mathrm{ton}_n^t - \exp ton_n^t \right| \tag{17}$$

The new model is mixed integer linear programming with absolute values. To solve this model, we need to add a new set of continuous variables (*Z*) and two new constraints (equations 19 and 20) which connect those variables to the objective function. Therefore the new objective function is:

$$Minimize \ \sum_{t=1}^{T}\sum_{n=1}^{N} Z_n^t \tag{18}$$

And the following two new constraints are added to the model:

$$\forall n \in N \,\&\, t \in T \rightarrow ext\,\mathrm{ton}_n^t - \exp ton_n^t \leq Z_n^t \tag{19}$$

$$\forall n \in N \,\&\, t \in T \rightarrow -(ext\,\mathrm{ton}_n^t - \exp ton_n^t) \leq Z_n^t \tag{20}$$

Which could be combined as: $-Z_n^t \leq (ext\,\mathrm{ton}_n^t - \exp ton_n^t) \leq Z_n^t$

5. Case study

The model is tested on a block-cave mining project which is designed based on 298 drawpoints. The best height of drawn (BHOD) is already calculated for the draw columns in which the total tonnage for the mineral reserve is 36.7 million tonnes of copper with the average grade of 1.24%. The total tonnage for draw columns fluctuates from 27,762 to 233,286 tonnes. The layout and the locations of the drawpoints for this mine is shown in Fig. 2. The constraints were implemented using the controlling parameters which are presented in Table 1.

The reserve will be extracted in 20 years with the mining capacity of 1 to 4 million tons of production per year in average grade of 1% to 1.4% of CU. Because of the operational considerations, 20 to 120 drawpoints can be active for each year of production. The model was run by a computer with configuration of i5-3470 CPU @ 3.20GHz and 8 GB installed memory (RAM). It took 42,732 seconds (11 hours, 52 minutes and 12 seconds) to find the integer optimal solution for the model at MIP gap of zero percent. Production during the life of mine is shown in Fig. 3.

Table 1. Controlling parameters for the constraints and the model

Parameter	Value	Unit	Description
T	20	Year	Number of periods (life of the mine)
G_{min}	1	%	Minimum allowable production average grade for CU per each period
G_{max}	1.4	%	Maximum allowable production average grade for CU per each period
M_{min}	1	Mt	Minimum production rate or mining capacity
M_{max}	4	Mt	Maximum production rate or mining capacity
ActMin	20	-	Minimum number of active drawpoints per period
ActMax	120	-	Maximum number of active drawpoints per period
MIPgap	0	%	Sets a 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	1E+12	-	An arbitrary big number
MaxDrawLife	7	Year	Maximum life of drawpoints
$\mathrm{exp}ton_n^t$	40,000	tonne	Expected tonnage of extraction for drawpoint ***n*** at period ***t***

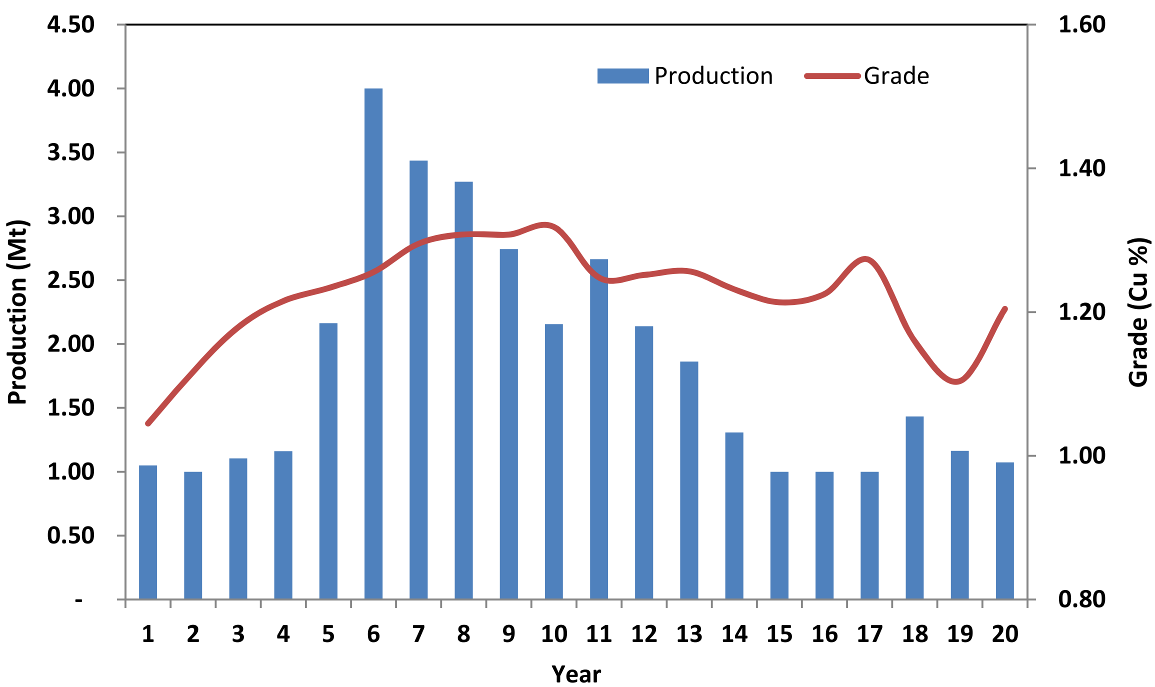

Fig. 3. Production and average grade during the life of mine

It can be seen that the production starts with the minimum capacity at the beginning of the project, increases to the maximum capacity in the years after and again close to minimum at the end of the life of mine. The resulted average grade for production can reasonably feed the processing plant (Fig. 3). Number of active drawpoints for different years during the life of mine falls in the boundary of the related constraint (Fig. 4).

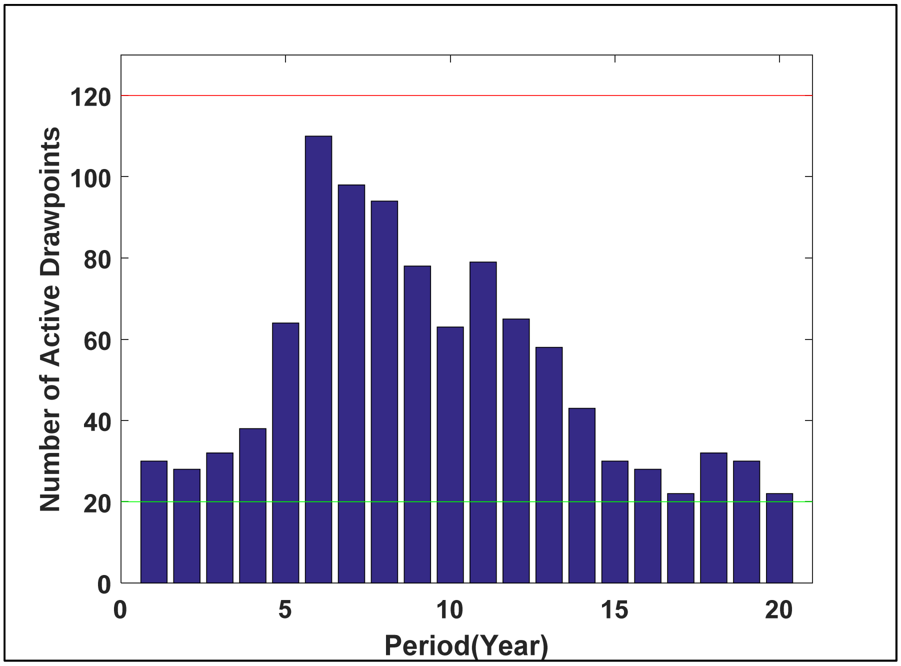

Fig. 4. Number of Active drawpoints during the life of the mine

The period (year) in which production from each drawpoint is started is shown in Fig. 5. It can be seen that the defined development direction and precedence of extraction is followed in the mine plan, extraction starts from the south-east and continues to the north west of the layout. This pattern can be seen by looking at the active and non-active drawpoints in each year as well (Fig. 6). Cumulative height of extraction (extraction profile) shows the cumulative height of extraction from drawpoints during the life of the mine (Fig. 7 to Fig. 10). The extraction moves smoothly from South-East to North-West by considering the neighborhood concept and reducing the horizontal mixing.

6. Discussion

Mathematical programming with absolute values can be used as a powerful tool for optimizing a problem when the goal is to minimize (maximize) a variance in the objective function. The original model for this research was a quadratic programming problem; the model was converted to a linear programming with absolute values. The resulted mine plan maintains the production rates as close as possible to the expected production which is defined in the objective function. This will reduce the horizontal movements of the material and as a result the dilution during the life of the mine. As the horizontal mixing reduces, the cave management and grade control is improved; in other words the operation is more predictable. The solution time for the converted model is significantly less than the original quadratic programming model. Results shows that although the size of the model will increase because of the conversion, the optimal mine plan can be achieved in a reasonable CPU time.

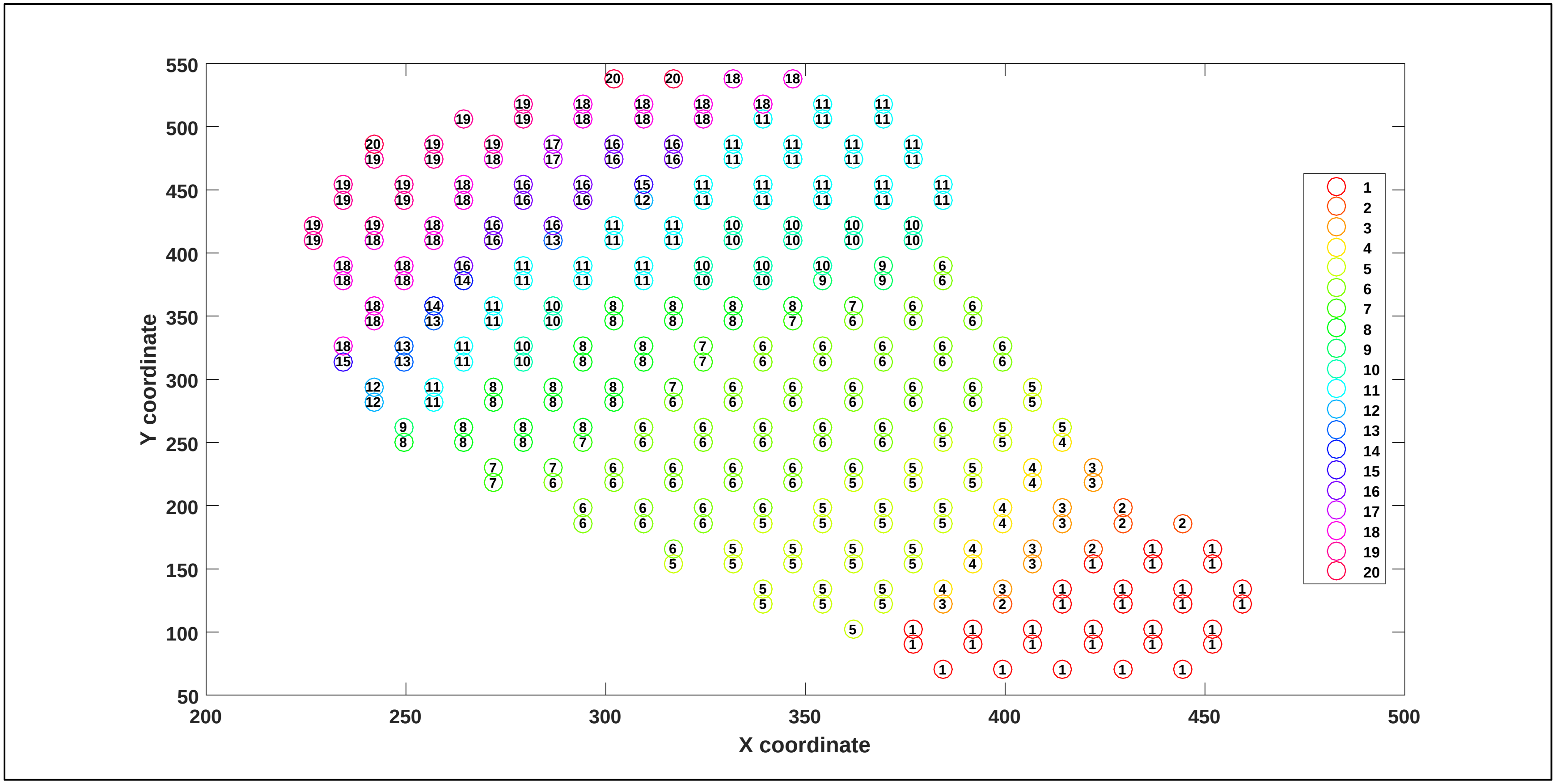

Fig. 5. Starting period (year) of production for drawpoints

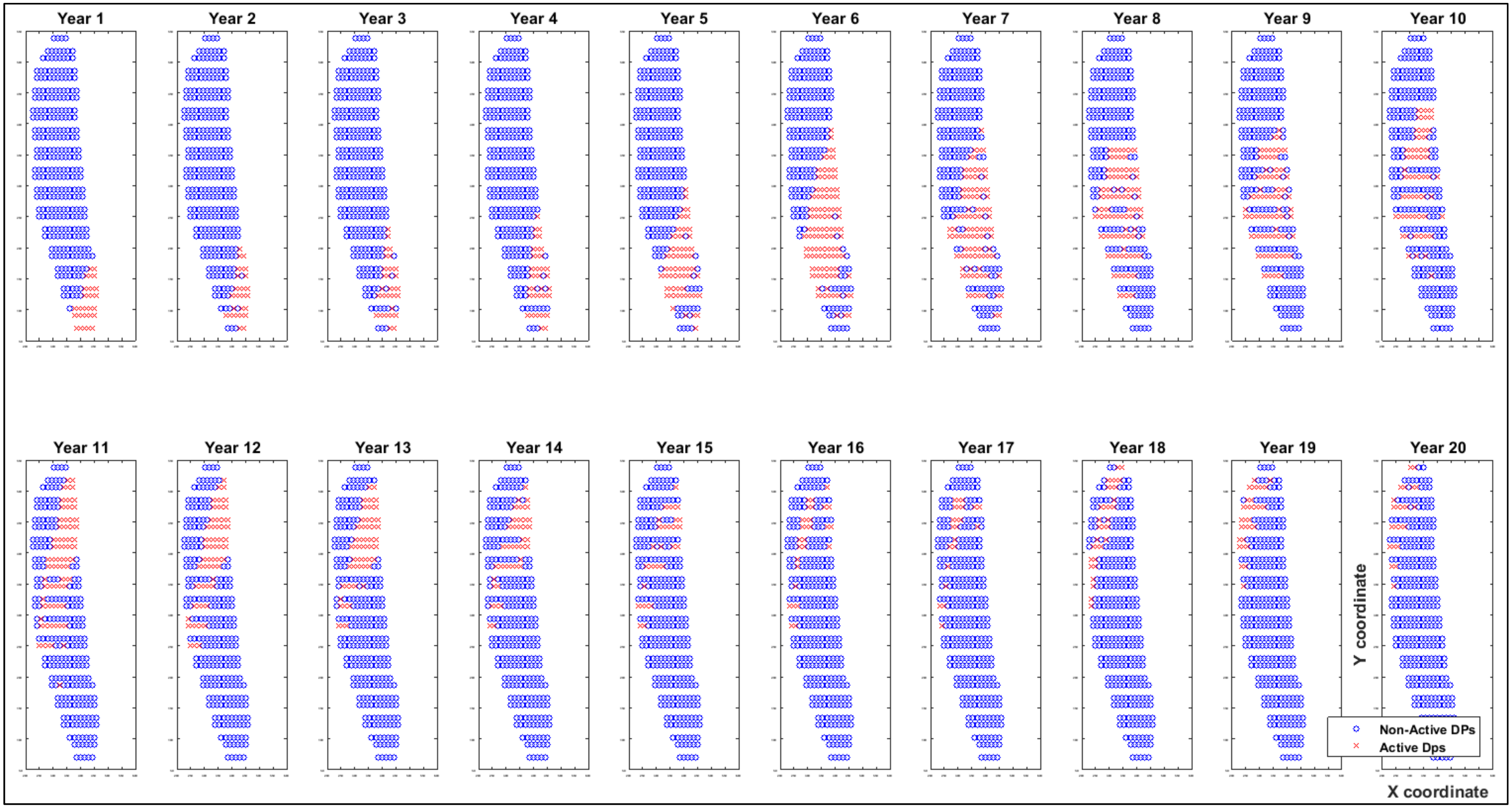

Fig. 6. Active drawpoints in the layout

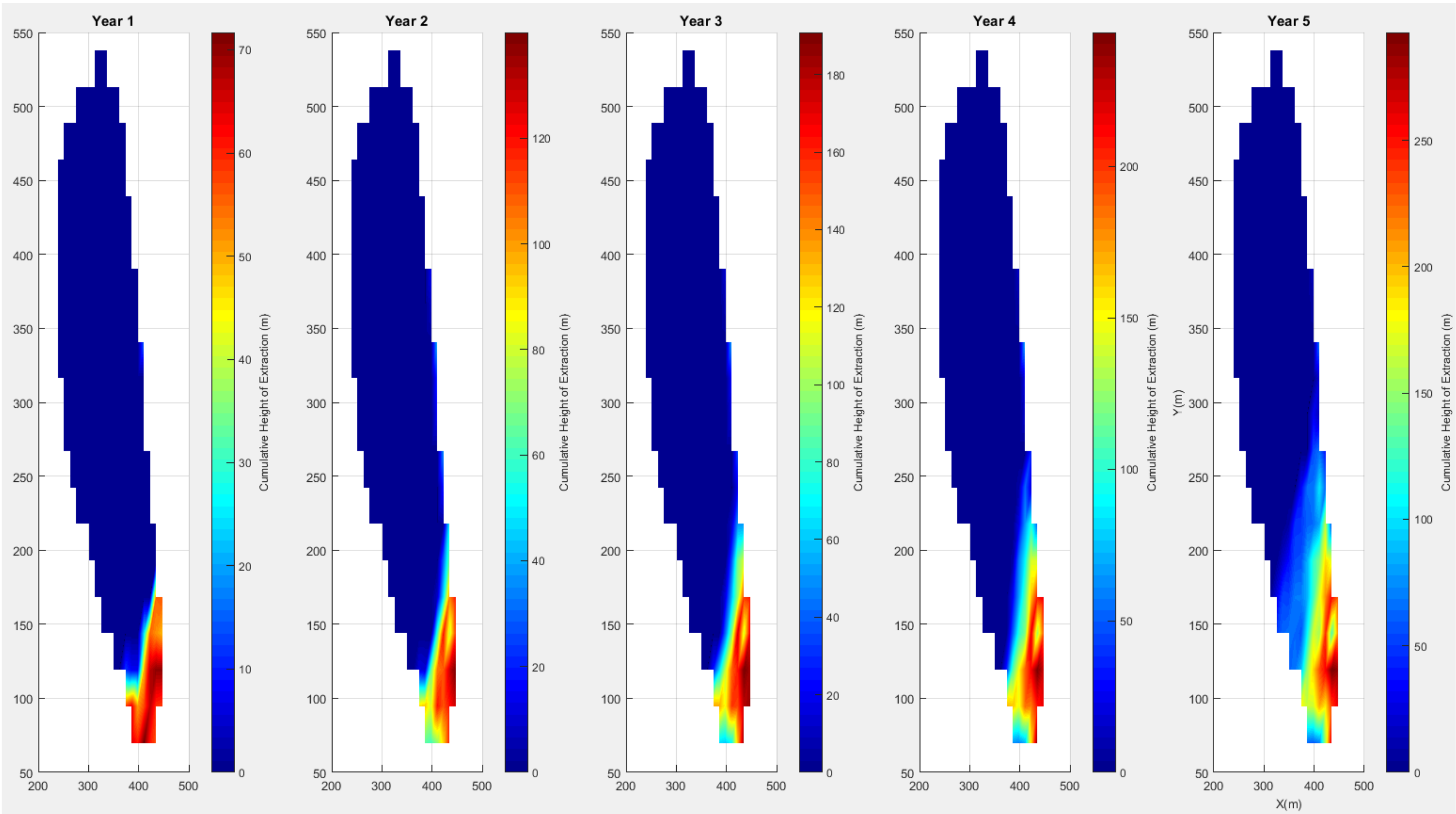

Fig. 7. Cumulative height of extraction or extraction profile during the life of the mine (Year 1 to 5)

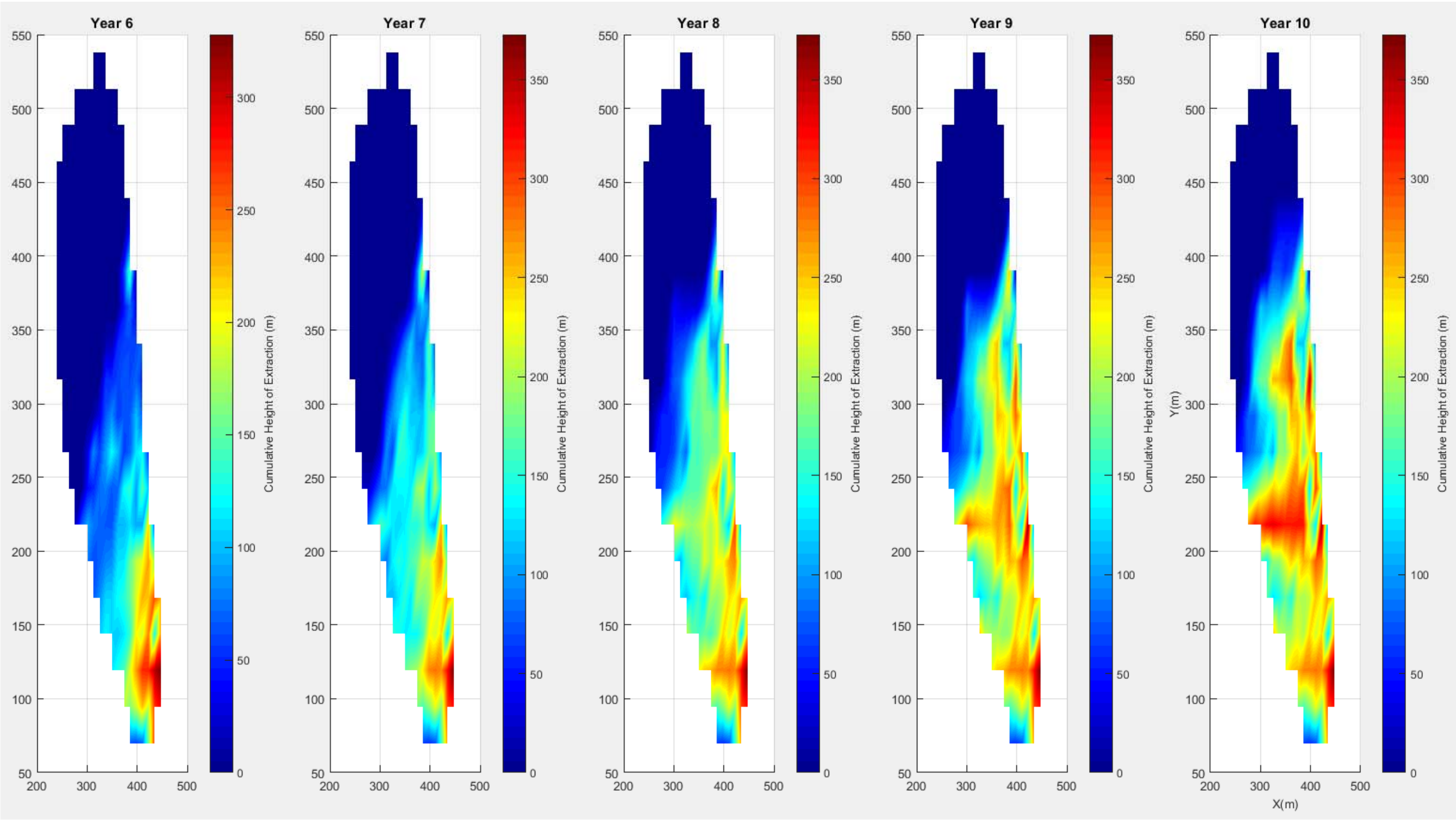

Fig. 8. Cumulative height of extraction or extraction profile during the life of the mine (Year 6 to 10)

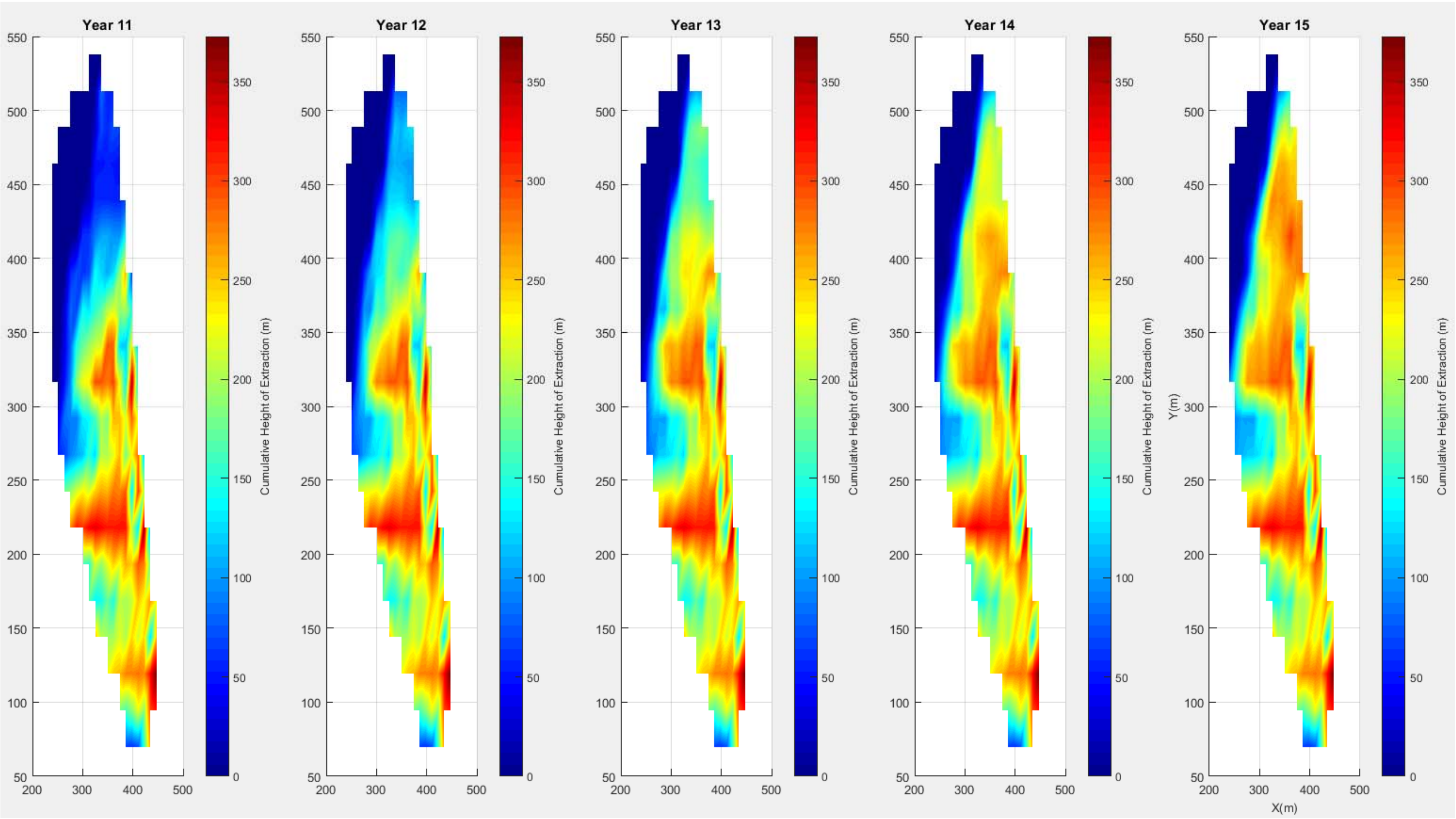

Fig. 9. Cumulative height of extraction or extraction profile during the life of the mine (Year 11 to 15)

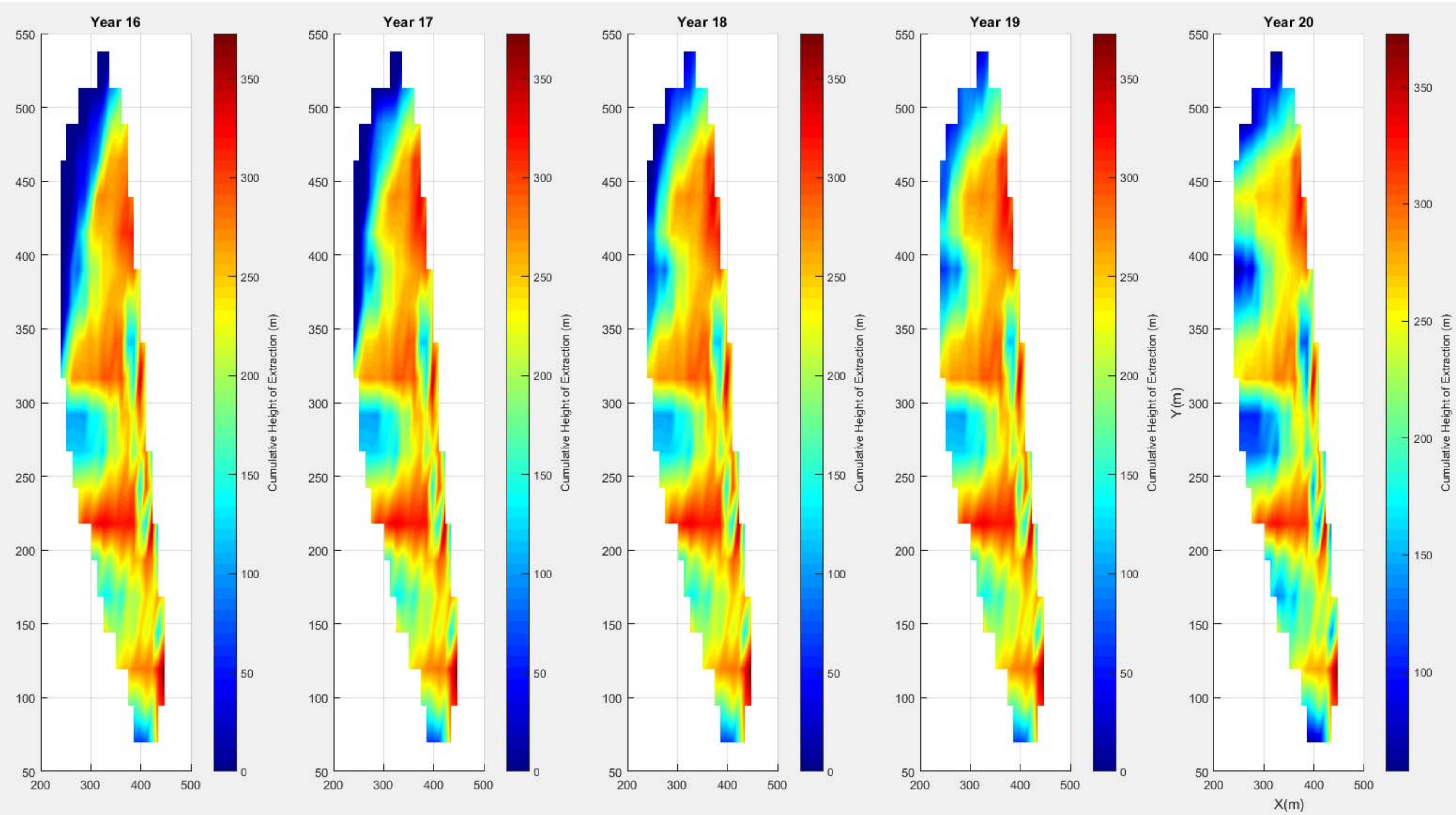

Fig. 10. Cumulative height of extraction or extraction profile during the life of the mine (Year 16 to 20)

7. References

[1] Chanda, E. C. K. (1990). An application of integer programming and simulation to production planning for a stratiform ore body. *Mining Science and Technology*, *11*(2), 165-172.

[2] Diering, Tony. (2000). *PC-BC: A Block Cave Design and Draw Control System.* Paper presented at the Massmin Brisbane, Australia.

[3] Guest, A. R., Van Hout, G. J., & Von Johannides, A. (2000). *An Application of Linear Programming for Block Cave Draw Control.* Paper presented at the MassMin, Brisbane, Australia.

[4] Khodayari, F., & Pourrahimian, Y. (2014). *Determination of the best height of draw in block cave sequence optimization.* Paper presented at the Caving 2014, Santiago, Chile.

[5] Khodayari, F., & Pourrahimian, Y. (2015). Mathematical programming applications in block-caving scheduling: a review of models and algorithms. *Int. J. of Mining and Mineral Engineering 2015 - Vol. 6, No.3 pp. 234 - 257, 6*(3), 234-257.

[6] Newman, A. M., Rubio, E., Caro, R., Weintraub, A., & Eurek, K. (2010). A Review of Operations Research in Mine Planning. *Interfaces, 40*(3), 222-245.

[7] Pourrahimian, Y., Askari-Nasab, H., & Tannant, D. (2012). Mixed-Integer Linear Programming formulation for block-cave sequence optimisation. *Int. J. Mining and Mineral Engineering, 4, No. 1*, 26-49.

[8] Pourrahimian, Y., Askari-Nasab, H., & Tannant, D. (2013). A multi-step approach for block-cave production scheduling optimization. *International Journal of Mining Science and Technology, 23*(5), 739-750.

[9] Rahal, D. (2008). *Draw Control in Block Caving Using Mixed Integer Linear Programming.* The University of Queensland.

[10] Rahal, D., Smith, M., Van Hout, G., & Von Johannides, A. (2003). The use of mixed integer linear programming for long-term scheduling in block caving mines. *Application of Computers and Operations Research ill the Minerals Industries, South African Institute of Mining and Metallurgy*, 123-132.

[11] Rubio, E. (2002). *Long term planning of block caving operations using mathematical programming tools.* The University of British Columbia.

[12] Rubio, E., & Diering, T. (2004). *block cave production planning using operation research tool.* Paper presented at the Massmin 2004, Santiago, Chile.

[13] Song, X. (1989). *Caving process simulation and optimal mining sequence at Tong Kuang Yu mine, China*.

Secondary Fragmentation Analysis in Block-caving mines: Assessment and Ranking of Critical Parameters Using Rock Engineering System (RES)

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Abstract

A profitable block or panel caving mining operation relies on the characteristics of the rock mass. Considering available literature on block-caving mining and application of this approach in some mines, it can be understood that assessment of rock mass caveability and fragmentation is one the most significant engineering design issues in geomechanics and mining industry. Conducted researches suggest that the caveability is not the only criterion to explain the fragmentation mechanism and probabilistic distribution of fragments in drawpoints. The identification of influencing parameters and fragmentation assessment are the prime geotechnical focus for all potential caving projects. In the caving operation, many factors, such as geometrical, geomechanical, environmental, and operational factors affect the caving and fragmentation performance. In this study, after discussing the caving process and identifying all effective parameters, the interaction matrix based on the rock engineering system (RES) is introduced to study the influencing parameters in rock mass fragmentation. The interaction matrix analyzes the interrelationship between the parameters affecting rock engineering activities. The interaction matrix for influencing parameters are established and coded by ESQ (Expert Semi Quantitative) approach. As a result, the high dominant or subordinate, and also the most interactive parameters, are introduced. The proposed approach could be a simple but efficient tool in the evaluation of the parameters affecting the fragmentation of rock mass in block-cave mines and as a result, useful in decision-making under uncertainties.

1. Introduction

The overall success and profitability of a block-caving operation will depend to a significant extent on the fragmentation produced in the ore-body during the caving process. The design and operating parameters influenced by fragmentation include (Laubscher 1990, 2000):

- Drawpoint size and spacing;
- Equipment selection;
- Draw control procedures;
- Production rates;
- Dilution entry into the draw column;
- Hangups and the need for secondary breakage with associated costs and damage;
- Staffing levels;
- Subsequent comminution processes and costs.

The prediction of rock fragmentation during block caving requires understandings of the natural fragmentation of the rock mass (caveability) and of the fragmentation processes that take place in the draw column. It is generally accepted that there are three levels of fragmentation, commencing with the in-situ blocks and then progressing to primary and to secondary fragmentation.

In-situ fragmentation is represented by the blocks that are naturally present within the rock mass before any mining activity takes place. They are completely determined by the network of discontinuities pre-existing in the rock mass. More precisely, the sizes and shapes of these blocks are a direct result of the geometry of the open discontinuities present within the rock mass. Incipient or healed discontinuities having finite shear and tensile strengths do not provide faces of in-situ blocks, but rather represent planes of weakness within the rock mass on which separation may occur in the primary and secondary stages of fragmentation. The orientation, size, spacing, condition and termination are the main parameters used to describe the overall network of discontinuities.

As the undercut is mined and caving is initiated, the blocks in the vicinity of the cave back that separate from the cave back define the ***primary fragmentation***. It will result from the loading conditions imposed on the rock mass in the vicinity of the cave back. Most failures at this stage can be expected to occur on the existing planes of weakness, but under high stress or stress caving conditions, fracture of intact rock may also occur. The extent of these failures will depend on the strength of both the discontinuities and the incipient rock blocks relative to the magnitudes and orientations of the imposed stresses. The primary fragmentation size distribution produced in this case is likely to be finer than in the case of subsidence caving in which gravity rather than induced stresses causes the detachment of blocks from the cave back. To a large extent, the network of pre-existing discontinuities will govern the formation of blocks during primary fragmentation.

Secondary fragmentation will occur as the caved ore resides in, and passes through, the draw column. The nature and degree of secondary fragmentation can be expected to vary with the stress regime within the caved mass, the composition and mechanical properties of the ore-body, the rate of draw, the height through which the material is drawn and the residence time in the draw column.

It is desirable that fragmentation models be developed to provide reliable estimates of fragmentation for use in mine planning. The basic requirement of any such model is to provide a measure of the range and distribution of the sizes of the rock blocks expected to be produced at the various stages of fragmentation and, in particular, those finally reporting to the drawpoints. For prediction of fragmentation in a mass caving mine, a comprehensive analytical approach named as Rock Engineering Systems (RES), has been implied which has the ability to analyzes the interactions between the parameters affecting a rock engineering activities.

2. Assessment and classification of effective parameters in fragmentation

To assess the in-situ-, primary-, and secondary fragmentation of the rock mass, it is necessary to evaluate the influencing factors on the initiation and propagation of caving and accurate characteristic of in-situ stresses of the rock mass. Furthermore we need to evaluate the effective parameters on secondary fragmentation through draw column. By investigations of the studies made on caveability and fragmentation, the effective parameters can be divided into four category including geomechanical, environmental, geometrical and operational factors.

2.1. Geomechanical factors

Geomechanical factors including the Geomechanical properties of intact rocks and discontinuities specification are considered as the main effective factors on the caveability and fragmentation of rock mass. The geomechanical factors of the rock mass are as follows:

2.1.1. Uniaxial Compressional Strength (UCS)

Normally, rocks having lower compressional strength can have higher caveability and fine fragmentation. Since the compressional strength of rocks in the study area are different, it is necessary to divide the operational zones to different parts from similar strength point of view and the analysis should be made on each part individually (Brown, 2003).

2.1.2. Elastic modulus

Elastic modulus of rock can be static or dynamic considering the loading rate on the rock. Dynamic elastic modulus is higher than static modulus. However, as strength of the rock increases, the value of dynamic elastic modulus will be closer to the static modulus. The elastic modulus of rock indicates the deformability of the rock and similar to compressional strength is one of the key parameters in caveability and fragmentation.

2.1.3. Frequency of discontinuities in rock mass

Rocks having higher fractures frequency have more caveability. The recent studies indicate the sensitivity of fragmentation to the volume intensity of joints (P_{32}) and the importance of critical intensity value in which the in-situ and intact rock mass is converted to rock mass which can be moved (Rogers et al., 2010).

2.1.4. Aperture

Aperture is called to the distance between the two walls of discontinuities that is measured perpendicular to main plane which can be filled with materials. Aperture can have effects on shears strength of discontinuities, water transmissivity and therefore can have effect on caveability of the rock mass.

2.1.5. Persistence

Persistence is the areal extent or size of a discontinuity, and can be crudely quantified by observing the trace lengths of discontinuities on exposed surfaces. The persistence of joint sets controls large scale sliding or 'down-stepping' failure of slope, dam foundation and tunnel excavation (Einstein et al., 1983). The persistence of discontinuity among other geometric parameters of the discontinuity has the highest effect on the rock mass strength (Einstein et al., 1983). The bridges between joints planes in an intact rock basically cause to have an increase in rock mass strength.

2.1.6. Roughness of discontinuity planes

Joint surface roughness is a measure of the inherent surface unevenness and waviness of the discontinuity relative to its mean plane. The roughness is characterized by large scale waviness and small scale unevenness of a discontinuity .Discontinuities having lower shear strength are suitable for caving because they have more intension for opening and caving (Mahtab and Dixon, 1977).

2.1.7. Filling discontinuity

Filling is material in the rock discontinuities. The material separating the adjacent rock walls of discontinuities. The wide range of physical behaviour depends on the properties of the filling material .In general, filling affects the shear strength, deformability and permeability of the discontinuities. Filling is effective on rock mass caveability because this factor has a significant role on rock mass strength (Mahtab and Dixon, 1977).

2.1.8. Weathering of discontinuity plane

The natural discontinuities normally suffered weathering and alteration, which in term, also change the degree of matching of the discontinuity surfaces. It was found that the mismatched discontinuities generally have much lower shear strength than matched (interlocked) ones.

Weathering and alteration of joint plane can decrease the roughness of joint plane and therefore can decrease the shear strength of discontinuity. Thus the alteration of joint planes can increase the potential movement of blocks on each other and increase caving and fragmentation.

2.2. Environmental factors

Although the rock mass caveability is highly dependent on natural geomechanical characteristics of rock, it is also affected considerably by environmental factors. The most important effective environmental factors in caveability are ground water and in-situ stresses.

2.2.1. Ground water

The presence of water in the area can reduce the friction between joints and increase of water pressure cause increase in the caveability. The origin of water can be from ground water resources or seasonal precipitation (Laubscher, 2000).

2.2.2. In-Situ stresses

The ratio of horizontal to vertical in-situ stresses has a considerable effect on the intensity of induced stresses in cave back, cave propagation and caving rate. Despite the existence of suitable structures and geomechanical characteristics of these structures for caving of rock mass, high stresses may limit the initial caving and its propagation in the deposit. If there is no low angle discontinuities in the rock mass, the high values of these stresses can lock the blocks and create the rock mass stability against caving propagation (Brady and Brown, 2005).

2.2.3. Fine fragments proportion

The ratio of fines to medium/coarse fragmentation needs to be noted, as a high percentage of fines will cushion the larger blocks and prevents further attrition of these blocks and reduce the secondary breaking effect.

2.3. Geometrical factors

Geometrical factors such as hydraulic radius of undercut, undercut height, and block height can cause variation of induced stresses in the cave back and its propagation, if the induced factors that are effective on caveability vary.

2.3.1. Geometry of undercut

Excavation of undercut is very important for creation of initial failure in caving. A successful undercutting cause breaking and downward vertical movement of rock mass and flow downward of fragmented rocks having suitable sizes to the drawbells. A weak undercutting, leads to deformation of pillars, formation of large dimension blocks and eventually leads to lack of initial caving (kendorski, 1978). Narrow rectangular undercuts with respect to other undercuts are more suitable for forming a stable arch.

2.3.2. Undercut height

Undercut height affects the amount of induced stresses, caving propagation, the amount of caved ore to be drawn out, time to the primary production, fragmentation, and initial costs (Laubscher, 2000).

2.3.3. Draw column height

Secondary fragmentation of caved ore occurs when the ore moves downward to the drawpoint. The caving stress is the load imposed on pillars and stationary particles by the arching and direct loading of superincumbent caved material. This is likely to be significant if the height of the cave column is appreciable and there is irregular draw. The drawdown of caved material results in the formation and breakage the arches (Dorador, et al., 2014).

The blocks undergo abrasion and breakage (i.e., secondary fragmentation), which increases with draw column height. This generates rounder block shapes and smaller particles, enabling different block shape configurations and finer broken ore size distributions.

2.3.4. Drawpoint geometry

The degree of fragmentation determines the size of the draw zone and hence the drawpoint spacing. It also influences the height of the drawpoint, the need for access for secondary breaking, the shape of the major apex, the LHD size and crushing requirements. Drawpoint and drawbell design are related to the degree of fragmentation of the ore and its flow characteristics.

However, the drawpoint spacing is also a function of fragmentation. The ellipsoid of draw concept can provide the basis for the selection of an initial spacing. The application of this approach requires knowledge of the shapes and dimensions of the ellipsoid of draw and/or the limit ellipsoid. This knowledge may be obtained from model experiments (e.g. Heslop and Laubscher 1981) or from measurements made in full-scale trials or operations.

2.4. Operational factors

Operational factors affect the caveability from technical and economical point of view. The orientation and speeds of undercutting and extraction level and suitable draw of the crushed ore from drawpoints are among the effective operational factors on fragmentation (Brown, 2003).

2.4.1. Undercut direction

The shape of ore-body, distribution of grade in the ore-body, in-situ stresses, difference between the ore strengths in different zones, main structures and their orientations in the deposit and also the existence of previous cave zones adjacent to the block, are effective on the selection of starting point and advancement direction of the undercut. If the deposit is long and narrow in horizontal plan, the direction of undercutting will be in longitudinal direction (Laubscher, 2000).

The direction of undercutting in relation to the direction of main stresses is effective on the intensity of boundary stresses. For this reason to reduce the surrounding stresses in the cave back undercuts are usually excavated in the direction of main stresses (Laubscher, 2000). Advancement of caving in the direction of maximum stress can cause caving to be easier, however, only the rock masses in which support systems are installed, can bear high boundary stresses (butcher, 2000).

2.4.2. Draw rate

Control of extraction rate considerably affects caving and fragmentation behaviour of ore (Brady and Brown, 2005; Kendorski, 1978). A low draw rate will result in time dependent failure of the blocks as they are subjected to the caving and arching stresses. This is particularly important in the early stage if good fragmentation is required. The draw rate is an important factor that creates the caving space. This rate should not be high so that it causes to create an air gap and will increase probability of airburst. Weak control of the extraction rate, leads to leaving some caved rocks adjacent to walls. This can support walls and reduce the effect of undercut level. Therefore it affects caveability.

2.4.3. Anisotropic draw rate

Irregular draw is often the result of having zones of well fragmented material available, allowing for high productivity from those drawpoints at the expense of the drawpoints with coarse material. Draw control management is required not only to maximize the recovery but also to improve the fragmentation.

A uniform draw over the whole mining area means little relative movement between rock blocks compared to when zones of interactive draw are drawn on a regular schedule of one shift or one day so that high- and low-pressure areas are set up to promote differential movement.

2.4.4. Air gap

Single blocks released from the cave back can align to form numerous block arrangements. The airgap height is a relevant parameter in this regard. In the case of a negligible airgap, the blocks released from the Cave back will have less chance to rotate and thus will retain their contact with adjacent blocks. This would lead to a tighter packing and smaller initial swell factor. In contrast, the presence of a sizeable air gap would facilitate a more disordered block arrangement, increasing the initial swell factor.

2.4.5. Broken ore density

The broken ore density (BOD), commonly related to the swell or bulking factor, is an important parameter for block-caving design. It is well known that the ore column density decreases (and swell factor increases) at the drawpoint due to the development of a loosening zone generated by ore extraction. However, the broken ore in the draw column also potentially experiences stress and density heterogeneities throughout, depending on the block properties (e.g., shape, aspect ratio, and size distribution).

This generates rounder block shapes and smaller particles, enabling different block shape configurations and finer broken ore size distributions. These smaller particles migrate downwards into the draw column increasing the BOD (Dorador, et al., 2014; Elmo, 2008).

3. Rock engineering systems (RES) approach

When designing a structure to be built on or in a rock mass for mining or civil purposes, it is necessary not only to consider individual factors such as the intact rock strength, fractures, stresses, excavation and support, but also how these all interact together. As a means of linking the rock mechanics principles to the rock engineering applications, it is appropriate to consider how such interactions can be characterized. For rock mechanics modelling and rock engineering design for a specific project, the relevant physical variables and the linking mechanisms are identified and then their combined operation should be considered. Also, all the relevant factors and their interactions should be taken into account. But this vital goal is unreachable without using a guide method (Hudson, 1992).

Hudson (1992) introduced the concept of RES for rock engineering application. In order to lower down the risks to an acceptable level, there should be a decreasing in uncertainty due to the deficiency of understanding of a system.

3.1. Interaction matrices

A systematic method for thinking about all the interactions is to list them in a matrix. This is the basic device used by the rock engineering systems (RES) approach. The principal factors considered relevant to the problem are listed along the leading diagonal of a square matrix (top left to bottom right) and the interactions between pairs of principal factors form the off-diagonal terms. Then off-diagonal terms are assigned values which describe the degree of influence of one parameter on the other parameter. The assignment of these values is called coding the interaction matrix and the results are determined by carrying out calculations on the columns and rows of the matrix. Fig. 1 shows that, the parameters A and B are located in the top left and low right cells, respectively. The top right location indicates the dominance of A on B, whereas the low left is vice versa (Hudson 1992).

As an example, a 4×4 interaction matrix is shown in Fig. 2. The leading diagonal terms are rock structure, rock stress, water flow, and construction. In each of the off-diagonal terms, one example of the potential interactions is shown. The information in these off-diagonal cells is illustrative rather than comprehensive at this stage. With N leading diagonal terms the matrix will have N×(N-1) off-diagonal mechanisms (Hudson and Harrison, 1997).

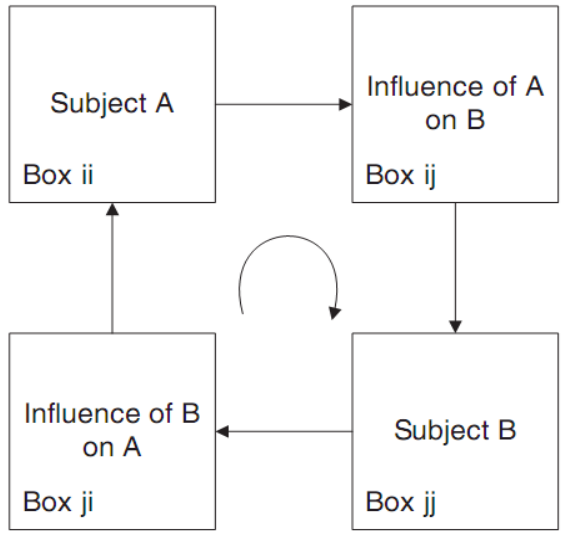

Fig 1. The principle of the interaction matrix (Hudson, 1992)

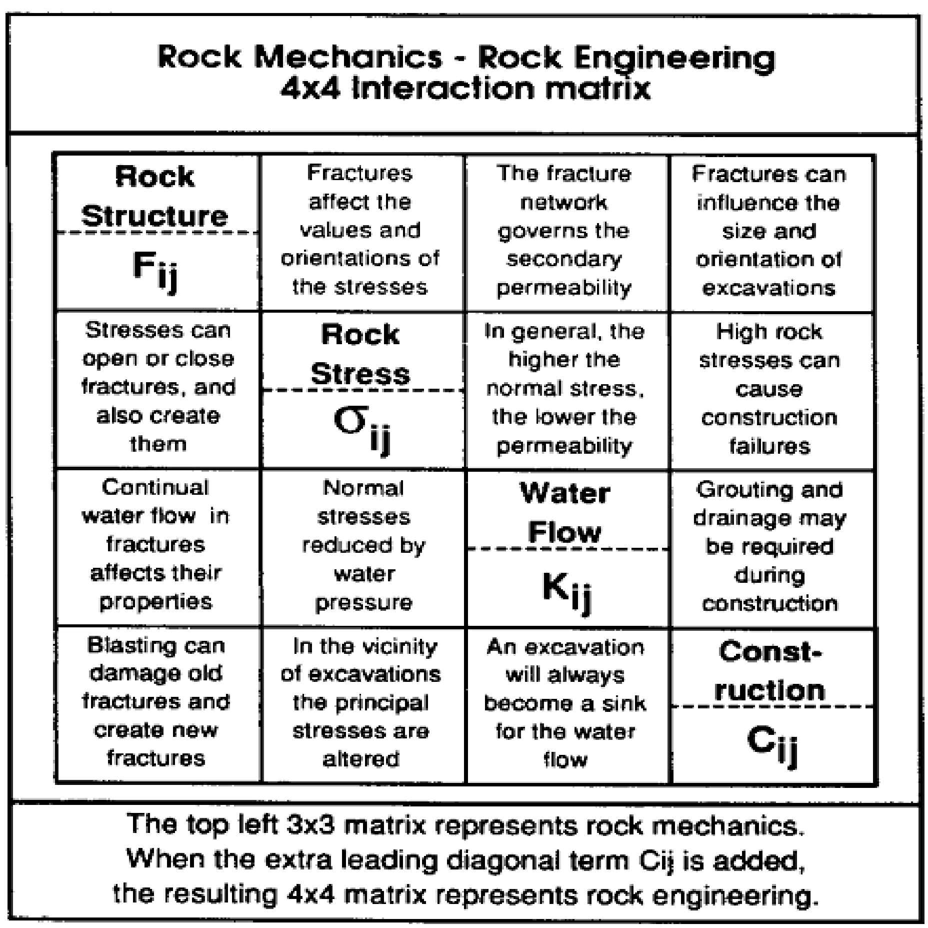

Fig 2. A 4×4 interaction matrix for mechanical parameters (Hudson and Harrison, 1997)

3.1.1. Coding the Interaction Matrix

The coding process is for propose of quantitation of interaction of parameters on each other and making up the related matrix. There are five main methods of characterizing the significance of the off-diagonal cells in the interaction matrix. These methods are:

a) Binary:

In binary method, mechanisms are switched on or off, as 1 or 0 respectively .The binary coding is naturally rather limited, but it can indicate the main links and the degree to which the matrix mechanisms are connected.

b) Expert semi-quantitative (ESQ):

The ESQ coding is helpful when the mechanisms cannot be quantified but an estimate of their significance can be made. The ESQ coding method has been used to establish parameter interactive intensity and dominance from the binary interaction matrix. There are five level of coding as shown in Table 1. In this method, coding is done by a technician or an expert, or a group of technicians.

Table 1. Concept of codes in ESQ

Code value	concept
0	No interaction
1	Weak interaction
2	Medium interaction
3	Strong interaction
4	Critical interaction

c) According to the slope of the linear xi vs xj state variable relation:

In this method, as it is shown in figure 3, coding is done by the case of the slope of the graph of parameters. If the graph of (Pi, Pj) is to be as a horizontal line, then Pj cannot be dependent on Pi. But if the relation between them is linear, then, their interaction could be coded in accordance to the slope of the line. Obviously, non-linearity among the factors enhance the persistence of difficulties in that most cases.

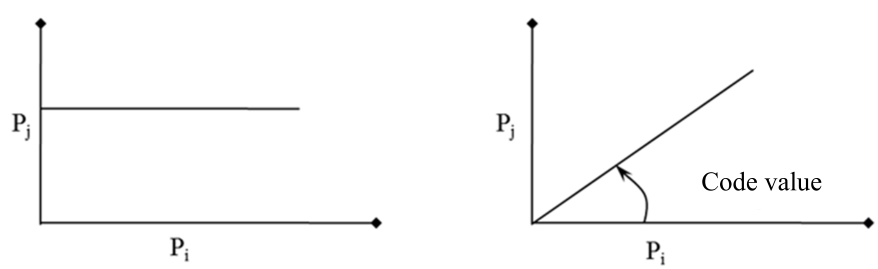

Fig 3. Coding the interaction matrix according to the slope of the line (Hudson, 1992)

d) Via solutions to partial differential equations:

In this method, the assumption is, all the mechanisms could be expressed as p.d.e (partial differential equations) in place of the entries of interaction matrix. Although it seems quite plausible to impose and apply second order partial differential equations solutions; yet, when the size of the matrix gets large, then the process would be very outreaching and cumbersome. In such cases the partial differential equation ought to be solved numerically by the aids of computers.

e) Via complete analysis of the mechanisms

In this method, it is assumed that all the mechanisms of the matrix are well known to a very high extend, therefore; the analysis of all the entries and consequently the behaviour of all interactions can be deliberated and determined.

Among all the various methods, the ESQ method, with keeping in mind all its weaknesses, has been wonderfully successful to an accepted level, and up to the present moment (at least for the sake of simplification and being so quick to reach the solutions) has had the most number of applications.

3.1.2. Cause-Effect Plot

After coding the matrix by inserting the appropriate values for each off-diagonal cell of the matrix, the sum of each row and column can be calculated. For each parameter (e.g. for the i-th parameter, Pi), the sum of its row values is termed the "cause" (Ci) value, whereas the sum of its column values is called the "effect" (Ei) value (see Fig. 4). Such information can be summarized as coordinates (Ci,Ei) on a cause–effect plot, where each point in the graph represents a particular factor Pi. In other words, Ci represents the way in which Pi affects the rest of the system and Ei represents the effect that the rest of the system has on Pi, which is related to the parameter being "dominant" (lower right region of the (C,E) plot) or to the system being "dominant" (upper left region). Besides, knowledge of Ci and Ei can be employed to compute the level of interactivity of each parameter Pi (computed as the sum of Ci+Ei) (Hudson 1992).

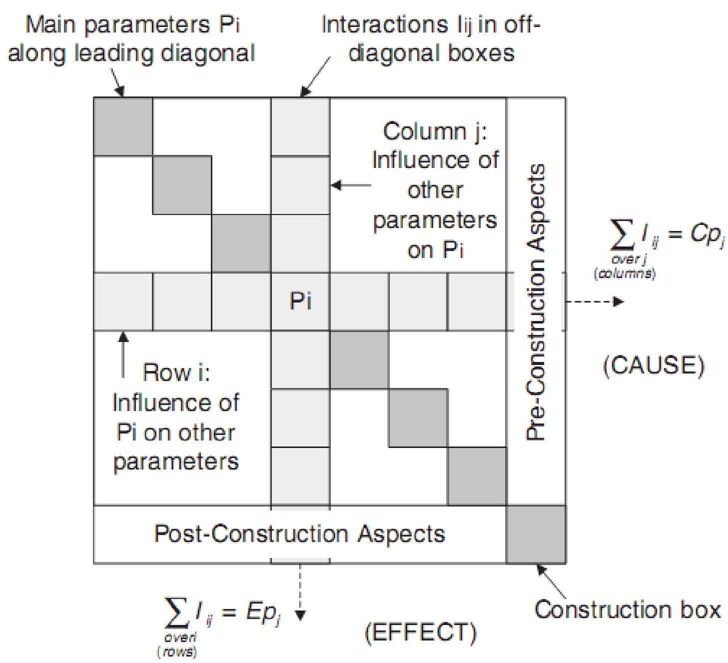

Fig 4. Summation of coding values in the row and column through each parameter to establish the cause and effect coordinates (Hudson and Harrison, 1992)

Obviously for each parameter, whatever the sum of the (C+E) be more, the more interaction intensity related to the whole system will be enhanced; whereas, the more subtracted number (C-E) is, the less dominance of the parameters on the system is revealed. The negative sign of (C-E) indicates the dominance of the system over the prevailing parameters. Different values for each of the parameters could be transformed on the graph of cause and effect. In Fig. 5, the graph (C,E) has been generalized to N observable parameters. In such case the parameters appear like a cloudy type distributed in E and C space which shows a high complexity of a system. It is very important to note carefully to the location of each points which represent the main parameters of the system to develop and enjoy usefully the theory of the systems, described in this section.

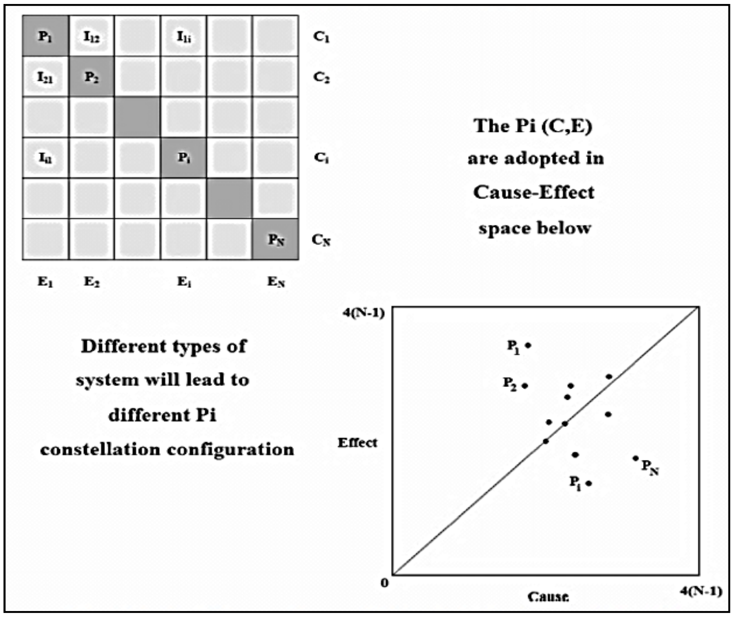

Fig 5. Cause versus effect diagram generalized for N parameters (Hudson, 1992)

3.2. Introduction of effective parameters on caveability in mass caving method

As it mentioned before, the effective factors on caveability can be divided in four main groups:

Geomechanical considerations

- Uniaxial compressive strength
- Elastic modulus
- Fracture Frequency of joints in rock mass
- Aperture of the joints
- Persistence
- Roughness of the joints surfaces
- Joint Filling
- Weathering of the joints surfaces

Environmental considerations

- In-situ Stresses
- ground water
- Fine ratio

Geometrical considerations

- Hydraulic radius

- Undercut height
- Draw Column Height
- Drawpoint geometry

Operational considerations

- Undercut direction
- Draw rate
- Anisotropic draw
- Air gap
- Broken Ore Density

3.3. Determination of interaction matrix

After investigation and definition of effective parameters on caveability, a square matrix (22×22) is formed as the interaction matrix as shown in Table 2. 21 effective parameters on fragmentation in addition to fragmentation potential are set on the main diagonal part of the interaction matrix. Then the other cells of the matrix are coded using expert semi quantitative method in which the view of experts in mass caving method is expressed.

The cause and effect values corresponding to each parameter can be represented as a point in a cause-effect coordinate system. Note that in this space the diagonal of the diagram is the locus of C=E. Along this diagonal and as we move away from the center of the coordinate system, the summation C+E increases. Then, the lines of equal interaction intensity (i.e. C+E values) can be plotted on the diagram allowing discrimination between less-interactive and more-interactive parameters. The cause-effect plot is helpful in understanding the behaviour of each parameter individually as well as studying the whole system. For example, the points tend to distribute perpendicularly to the C=E diagonal show low level of interactivity between parameters, whereas a high interactivity will result in the points distributed along the main diagonal (Mazzoccola and Hudson, 1996). So as shown in Fig. 6, filling has the least interaction in system and in-situ stresses, caveability and drawpoint geometry are the most interactive parameters respectively. Also it is shown that fracture frequency, in-situ stresses and uniaxial compressive strength are the most effective (dominant) parameters on system respectively and air gap is the most subordinate parameter in system (have minimal impact on system).

As shown in Fig. 6, a large data scatter along the main diagonal is observed, which mean a high level of interactivity between parameters.

The values of cause, effect, and interaction intensity,(C+E) for each parameter is displayed in a column chart in figure 7. Considering the column chart shown in Fig. 7. The obtained results show:

i. In the class of geomechanical parameter, fracture frequency and uniaxial compressive strength have the highest effect on the fragmentation. Moreover, among the parameters in this group roughness and alteration of joints are the most dominated by system.
ii. In the class of environmental factors, in-situ stresses have the highest cause and the highest effect and are the most interactive parameter in the system as well.
iii. In the class of geometric factors, the drawpoint geometry has the highest cause, effect and interaction intensity in the system among the factors in this class.
iv. Among operational factors, the factor of draw rate has the highest cause and the highest effect and also is the most interactive parameter in this class.

Table 2. Interaction matrix of dominating parameters over caveability and fragmentation in block caving

																							Cause	C+E
	ucs	1	1	0	2	2	0	3	3	1	3	2	1	0	2	0	0	0	4	1	3	3	32	42
	1	Elastic modulus	2	1	1	1	0	1	3	0	2	2	1	1	2	0	2	1	3	1	1	1	27	29
	2	0	ff/m	0	2	0	0	2	3	4	4	3	2	0	3	0	2	2	2	2	4	4	41	47
	2	0	0	Aperture	2	3	2	2	2	3	3	0	2	0	0	0	1	0	0	2	2	1	27	35
	0	0	1	2	persistence	2	1	1	2	3	3	2	1	1	1	0	2	1	2	0	2	2	29	40
	0	0	0	0	1	Roughness	0	0	1	0	3	0	0	0	0	0	0	0	2	0	3	2	12	27
	1	0	0	2	0	2	Filling	1	1	1	2	0	0	0	3	0	0	0	0	0	1	2	16	21
	3	0	0	1	0	3	0	alteration	1	3	3	0	0	0	2	0	0	0	1	1	2	1	21	36
	0	0	2	2	3	0	0	1	Stress	3	4	4	1	0	1	0	2	1	2	4	3	2	35	80
	1	1	0	0	0	2	2	3	2	Water	2	0	3	3	1	2	1	1	1	1	2	2	30	53
	0	0	0	0	0	0	0	0	4	0	HR	0	2	1	0	2	0	1	2	3	4	1	20	60
	0	0	0	0	0	0	0	0	3	1	3	Undercut Height	1	0	0	1	0	2	2	0	4	3	20	33
	0	0	0	0	0	0	0	1	3	0	1	0	Draw rate	3	2	4	3	2	3	1	1	2	26	59
	0	0	0	0	0	0	0	0	2	0	1	0	2	Uniso draw	3	2	2	2	2	1	0	3	20	44
	0	0	0	0	0	0	0	0	2	2	0	0	2	2	Fine ratio	0	0	3	2	2	0	3	18	51
	0	0	0	0	0	0	0	0	2	0	0	0	2	2	3	D C H	4	3	3	0	0	2	21	39
	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	4	Air gap	3	0	0	0	4	14	36
	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	B O D	2	2	0	3	13	43
	0	0	0	0	0	0	0	0	1	0	0	0	4	3	1	2	3	3	Drawpoint Geometry	3	0	2	22	63
	0	0	0	0	0	0	0	0	3	0	3	0	3	2	1	0	1	1	2	Undercut Direction	4	2	22	52
	0	0	0	0	0	0	0	0	4	2	3	0	2	1	2	1	2	4	3	1	Caveability	3	28	65
	0	0	0	0	0	0	0	0	2	0	0	0	3	2	3	0	2	3	4	3	1	fragmentation	23	69
Effect	10	2	6	8	11	15	5	15	45	23	40	13	33	24	33	18	27	30	41	30	37	46		

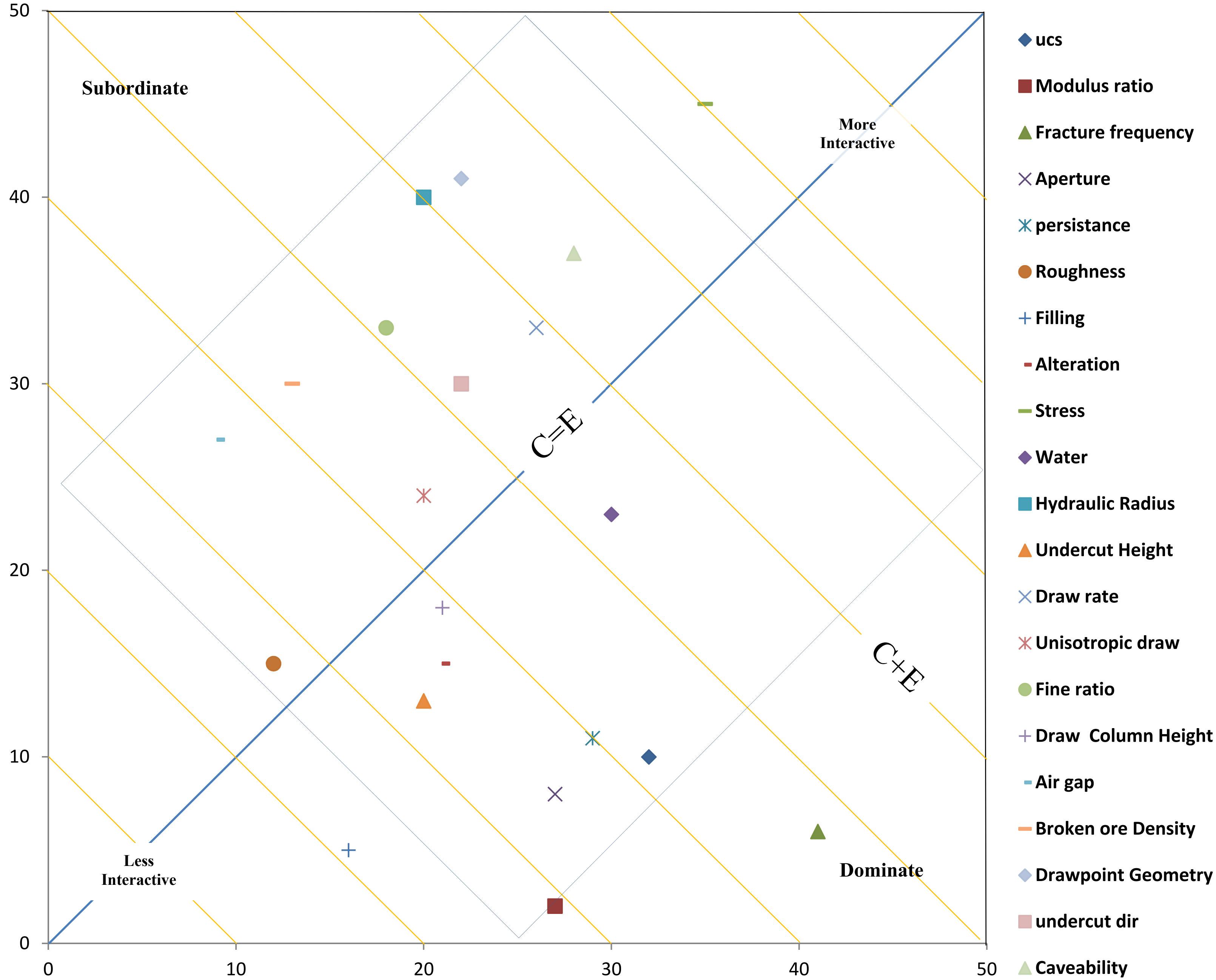

Fig 6. Cause- effect diagram for ranking fragmentation

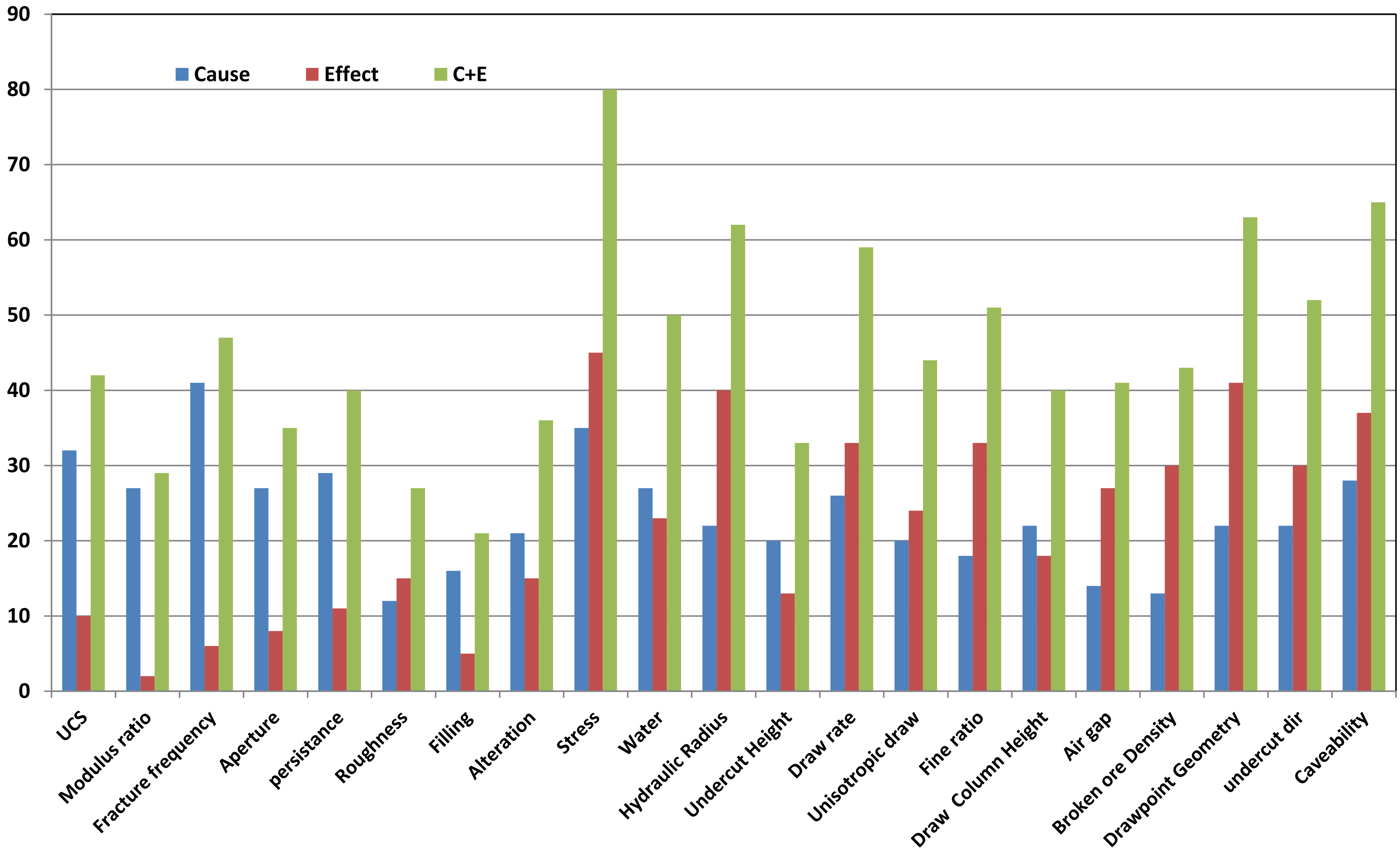

Fig 7. The histogram of domination of parameters on fragmentation

In general, as can be seen from the column chart in Fig. 7, the most dominant parameters, affecting fragmentation are: fracture frequency, stress, uniaxial compressive strength of intact rock, and persistence, respectively.

As noted, three parameters out of the four parameters that have the highest cause on the system are among geomechanical parameters. Therefore, we can surely say that geomechanical parameters and specially parameters related to discontinuities specifications have the highest effect on the system.

Geometrical and operational parameters in addition to having the highest effect compared to the other factors have also the highest interaction in the system compared to other classes of the factors.

3.4. The determination of fragmentation Index (FI)

By the time an interaction matrix is made and a (C+E) graph is drawn (the interaction intensity), a general function that covers all the effective parameters on the system could be obtained. In general, systems that are more under the effects of parameters, the more instability is expected for them, Since a little change in one parameter, makes it probable to observe a drastically changes in the behaviour of the whole system. By observing the histogram of domination of parameters in Fig. 7, it could be noted that in the most parameters the interaction intensity, (C+E), is far above the mean value. Therefore, all the parameters should be noted carefully in determining and designation of fragmentation index. In each project based on RES, each single parameter has a particular weight and portion considering the interaction matrix regardless of the real quantity of each parameter. The weight or portion of the parameter P_i, is calculated by equation (1). By dividing the portion of each parameter to the largest score that could be gained by parameters in the scoring system of the interaction matrix, the normalized weight of that parameter is obtained by equation (2).

$$W_{P_i} = \frac{(C+E)_i}{\sum_{i=1}^{n}(C+E)_i} \times 100 \tag{1}$$

$$a_i = \frac{1}{MP_{ij}} * \frac{(C+E)_i}{\sum_{i=1}^{n}(C+E)_i} \times 100 \tag{2}$$

In which;

W_{P_i}	the weight or the portion of the parameter p_i, percent wise,
MP_{ij}	the maximum score that the parameters could receive in the scoring system
$(C+E)_i$	the sum of the dominance and effect of the ith parameter
$\sum_{i=1}^{n}(C+E)_i$	the sum of Cause and Effect of all the parameters

For each certain block caving mine, the related score to each parameter should be determined. To clarify, a table is presented for some effective parameters. In Table 3, the parameters are categorized in five classes. It must be clear that the classification of parameters of the system is very important as far as the outcome results are concerned, due to the fact of their effectiveness on the entire system. Hence, there has been an extensive and serious study on the variation of the chosen parameters in the block-caving mines under progress. For some other parameters it is not possible to make a classification like Table 3, due to low case study and real data from previous works. In such situation we should use experts' comments. Table 4 shows the evaluation of quality of joint orientation in block-caving mines.

The fragmentation Index (FI) for each mine block should be under taken individually and separately; even for the blocks with different sections and various conditions, the index should be calculated for each section.

In order to know whether the gained fragmentation index indicates appropriate fragmentation or not, it requires real data from different block-caving operations for preparing a classification into at least three fragmentation indices; well fragmented, fair fragmented and poor fragmented. It should be noted that this part of the research has not finished yet.

4. Conclusion

After ranking of the parameters are done properly by RES method and knowledge about the amount of dominance, subordinate and interaction intensity of the parameters on the whole system, so that in case of necessity some proper changes in parameters could take place to conduct the system toward desired goals.

In order to select appropriate parameters to improve the condition of the system, the first step is to do the ranking based upon the dominance of the parameters themselves. Logically, preference is with those which have more dominant on system.

The interaction of a parameter with the rest of the system is on the second importance. Although, it must be noted that the interaction of on parameter with the rest of system, has to in the direction so that the whole system become in a better condition and it reaches to its desired goals.

The final precedency of the parameters is to be done considering technological and economic aspects. In the last stage, before enhancing the decisions to the final operations, it is wise to estimate the amount of changes in the system, using the obtained index by RES method.

The ranking of the parameters based on the interaction intensity are in-situ stress, drawpoint geometry, hydraulic radius, draw rate, undercut direction, and fracture frequency, respectively. In order to make some changes in fragmentation and caveability, some changes should be done in those parameters which have more dominancy, beside more interaction intensity in system. Whatever the dominance and interaction intensity of parameters be greater, it is possible to make greater change in system with a little change in that parameter. So in case of fragmentation in block caving, according to the rankling of the parameters the following changes can be suggested:

For in-situ stresses, in the environment with high horizontal stresses, there could be a way to get around the problem by excavation of high slots at the boundary of the blocks in order to increase the caveability.

In the group of geometrical parameters, the fragmentation, dilution, and mud rush will get in better condition by inducing the changes in the geometry of drawpoints. The primary fragmentation could be in controlled by changing the hydraulic radius through increasing the ratio of width to the length of the undercut or by creating a larger undercut or even changing the method of undercutting.

In the group of operational parameters, as mentioned before, the change in the draw rate and also anisotropic draw from the adjacent drawpoints help to control the fragmentation. The improvement in fragmentation related to the direction of undercutting is also doable, by advance in the direction of maximum main stress. The fracture frequency could be changed in order to induce primary fragmentation and initiating of caving, by using some artificial methods; like hydraulic fracturing and blasting.

It's always possible to do some proper changing for one or few parameters in order to get close to the desired fragmentation. Selecting the proper parameter, amount of change and estimation of consequence fragmentation could be done by calculating the fragmentation index (FI) after each change in parameters and comparison of the gained FI with FI of an existing mines. Evidently, for the determination of the parameters in order to create a change in any system, the economic and technological aspect of those changes ought to be under consideration.

Table 3. The classification of the parameters in the system developed to estimate fragmentation

Parameter	Unit	Class				
		0	1	2	3	4
UCS	MPa	>250	100-250	50-100	25-50	<25
Modulus ratio	-	<200	200-300	300-400	400-500	>500
Fracture Frequency	1/m	<1.6	1.6-5	5-12	12-20	>20
Aperture	mm	Without opening	<0.1	0.1-1	1-5	>5
Persistence	m	<1	1-3	3-10	10-20	>20
Roughness	-	Very rough	Rough	Rather rough	smooth	Slickensided
Filling	mm	Without filling	Very hard filling<5mm	Hard filling >5	Soft filling >5	Very soft filling <5
Weathering	-	Without weathering	Few weathering	Rather weathered	weathered	Strongly weathered
In-situ stresses	MPa	<50	50-100	100-200	200-400	>400
Ground water	-	Completely Dry	Damp	Wet	Dripping	Flowing
Hydraulic radius	m	<15	15-30	30-45	45-60	>60
Undercut height	m	<13	13-15	15-17	17-20	>20
Draw column height	m	<100	100-150	150-200	200-250	>250
Undercut direction	-	Very unfavorable	unfavorable	fair	favorable	Very favorable
Draw rate	$t/day/m^2$	<0.3	0.3-0.67	0.67-0.75	0.75-0.8	0.8-1

Table 4. The evaluation of the quality of oriented joints in the block caving mines

Category	Description
Very undesirable	Two joints sets or less with the slope of 60 to 90° degree.
Undesirable	Two joint sets. One set is relatively perpendicular. The others with the slope of 30 to 60°
Fair	At least three joint sets. One group with slope of 10 to 30 degree (the direction of the slope is against the direction of undercut). Two sets with slope above 60°
Desirable	At least three joint sets. One set with the slope of 10 to 30 degree (the direction of the slope is the same as that of the undercut). Two sets with cross each other with slope above 60°
Very desirable	At least three joint sets. One set with the slope of 0 to 10 degree. Two others crossing each other with slope above 60 °.

Table 5. Determination of the fragmentation index (FI)

	P_i	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	P_{20}	P_{21}
Proportion of P_i (%)	$\frac{(C+E)_i}{\sum_{i=1}^{n}(C+E)_i} * 100$	4.38	3.02	4.90	3.65	4.17	2.81	2.19	3.75	8.33	5.21	6.46	3.44	6.15	4.58	5.31	4.17	4.27	4.48	6.56	5.42	6.77
Normalized proportion of P_i	$a_i = \frac{1}{MP_{ij}} * \frac{(C+E)_i}{\sum_{i=1}^{n}(C+E)_i} * 100$	1.1	0.76	1.23	0.91	1.04	0.7	0.55	0.94	2.08	1.3	1.62	0.86	1.54	1.15	1.33	1.04	1.07	1.12	1.64	1.36	1.69
Score of P_i for a special case study (assumed)	p_{ij}	3	2	4	3	3	3	2	3	2	1	2	2	2	3	0	4	0	1	2	1	4
Proportion of parameter P_i in (FI)	$a_i * p_{ij}$	3.3	1.52	4.90	2.73	3.12	2.1	1.1	2.82	4.16	1.3	3.24	1.72	3.08	3.45	0	4.16	0	1.12	3.28	1.36	6.76
Fragmentation index (FI)	$FI_j = \sum_{i=1}^{n} a_i * p_{ij}$											55.22										

5. References

[1] Brady, B., & Brown, E. T. (2005), “Rock Mechanics for underground mining”, third edition. Springer Science and Business Media, Inc.

[2] Brown, E. T. (2003), “Block Caving Geomechanics”, Australia. Julius Kruttschnitt Mineral Research Centre .

[3] Butcher, R. J. (2000), Block Cave Undercutting Aims, Strategies, Methods and Management.

[4] Dorador, L., Eberhardt , E., Elmo, D., Norman, B. (2014). “Influence of secondary fragmentation and column height on block size distribution and fines migration reaching drawpoints”, *3rd International Symposium on Block and Sublevel Caving (Caving 2014), Chile,* pp.128-137.

[5] Einstein, H. H., Veneziano D., Baecher G. B., O’Reilly K. J. (1983), “The effect of discontinuity persistence on a rock slope stability”, *International Journal of Rock Mechanics and Mining Sciences, 20, 5*, pp. 82-94.

[6] Hudson, J. (1992), “Rock Engineering Systems: Theory and Practice”, Ellis Harwood Ltd, Chchester.

[7] Hudson, J., & Harrison, J. (1992), “A new approach to studying complete rock engineering problem”, *Quarterly Journal of Engineering Geology,* pp. 93-105.

[8] Kendorski, F. S. (1978), “Cavability of ore deposits”, Mining Engineering, pp. 628-631 .

[9] Laubscher, D. H. (2000). A practical manual on block caving. Section 6 - Cavability. International Caving Study, Julius Kruttschnitt Mineral Research Centre, University of Queensland, Australia.

[10] Laubscher, D.H., (1981), “Selection of Mass Underground Mining Methods, Design and Operation of Caving and Sublevel Stoping Mines”, SME. AIME, Stewart, New York, P 23- 38.

[11] Laubscher, D.H., Jakubec, J., (2000), “The MRMR Rock Mass Classification for Jointed Rock Masses”, Chapter 57, pp 475–481, Society of Mining Engineers, AIME, 2000.

[12] Laubscher. D. H., (1990), “A geomechanics classification system for the rating of rock mass in mine design”, J. S. Afr. *Inst. Min. Metall. vol. 90, no.10*

[13] Mahtab, M. A., & Dixon, J. D. (1977), “Influence of rock fractures and block boundary weakening on cavability”, *Trans Society of Mining Engineers of the AIME*, pp. 6-12 .

[14] Mazzoccola, D., Hudson, J. (1996). A comprehensive method of rock mass characterization for indication natural slope instability. *Quarterly Journal of Engineering*, pp. 37-56.

[15] Rogers, S., Elmo, D., Webb, G., & Catalan, A. (2010), “A DFN based approach to defining insitu, primary and secondary Fragmentation distributions for the Cadia East panel cave project”. *Proceedings of 2nd Int. Symp. on Block and Sublevel Caving, Perth, Australia,* pp. 425-439.

[16] A. Vyazmensky, A., Elmo, D., Stead, d., and Rance, J., (2008), ‘‘Numerical analysis of the influence of geological structures on the development of surface subsidence associated with block caving mining”. *Proceeding of Massmin 2008, lulea, Sweden*, pp.857-867.

Optimization of Block-cave Production Scheduling under Grade Uncertainty

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Abstract

The initial evaluation of a range of levels for starting the extraction of block-cave mining is an important issue. To do this, it is necessary to consider a variety of parameters including extraction rate, block height, discount rate, block profit, cost of mining and processing and revenue factors. Afterwards, production scheduling plays a key role in the entire project's profitability, determining the amount, grade and sequence of the extraction during the mine life by optimizing particular objectives in the presence of operational and technical constraints. To consider grade uncertainty, a set of simulated realizations of the mineral grade is modeled based on stochastic sequential simulation.

The purpose of this paper is to present a methodology to find the best extraction level and the optimum sequence of extraction for that level under grade uncertainty. Maximum net present value (NPV) is determined using a mixed-integer linear programming (MILP) model after choosing the best level 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 favored because of their low-cost 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. 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 central criterion on 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 and planning expectations and, as a result, the net present value (NPV) of the project (Koushavand and 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. Dowd (1994) presented a risk-based algorithm for surface mine planning. In the algorithm, for different variables such as commodity price, processing cost, mining cost, investment required, grade and tonnages, a predefined distribution function was implemented. Several types of schedules were generated for a number of realizations of the grades. This methodology produces various schedules that account for grade uncertainty. Ravenscroft (1992) and Koushavand and Askari-Nasab (2009) used simulated ore-bodies to show the influence of the grade uncertainty on production scheduling. Ramazan and Dimitrakopoulos (2004) used a mixed-integer linear programming (MILP) model to maximize the NPV for each realization. Then they calculated the probability of extraction of a block at each period. These probabilities are the input of a second stage of the optimization, which is necessary in order to generate one schedule at the end. Dimitrakopoulos and Ramazan (2008) presented a stochastic integer programming (SIP) model to generate optimal production schedules. This model considers multiple realizations of the block model and defines a penalty function that is the cost of deviation from the target production. This cost is calculated based on the geological risk discount rate which is the discounted unit cost of deviation from the target production. The objective function is to maximize the NPV under a managed risk profile. Leite and Dimitrakopoulos (2007) implemented an approach that incorporates the geological uncertainty in the open-pit mine scheduling process. This new scheduling approach is based on a simulated annealing (SA) technique and stochastically simulated representations of the ore-body. Albor and Dimitrakopoulos (2009) developed a method which is based on scheduling with an SA algorithm and equally probable realizations of a mineral deposit. To generate production schedules, the equally probable realizations are utilized to minimize the possibility of deviations from production targets. Sabour and Dimitrakopoulos (2011) presented a procedure that combines geological uncertainty and operational flexibility in the design of open-pits. When designing an optimal production schedule and ultimate pit limit, Asad and Dimitrakopoulos (2013) considered both geological uncertainty and commodity prices with respect to the production capacity restrictions. Two-stage stochastic integer programming (SIP) is used in an optimization model to consider uncertainty (Ramazan and Dimitrakopoulos, 2013). Lamghari and Dimitrakopoulos (2012) also considered metal uncertainty in the open-pit production scheduling problem using a metaheuristic solution approach based on a Tabu search. Lamghari et al. (2013) proposed two variants of a variable neighborhood decent algorithm to solve the open-pit mine production scheduling problem under geological uncertainty. Maleki and Emery (2015) have worked on the joint simulation of copper grade and rock type in a given deposit. To conduct the joint simulation, they implemented multi-Gaussian and pluri-Gaussian models in a combined form. They studied three main rock types with various grade distributions in which three auxiliary Gaussian random fields were considered. One of the rock types was used for copper grade simulation and the other two for rock-type simulation. Moreover, they looked at cross correlations between these Gaussian random fields before reproducing the dependence between copper grade and rock types.

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 mining outline and 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), MILP, and quadratic programming (QP). LP is the simplest program for modelling and solving. Table 1 shows some of the applied mathematical methodologies in block-caving production scheduling.

This paper will introduce a method designed to find the best level for initializing extraction according to the maximum discounted ore profit under grade uncertainty. Several realizations are modeled by using geostatistical studies to consider grade uncertainty. The production schedule is generated for the given advancement direction and in the presence of some constraints at the chosen level.

2. Methodology, assumption, and notations

The ore-body 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 profit data.

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 best level of extraction is found. Finally, the optimal sequence of extraction is determined to maximize the NPV for each realization. Fig 1 shows the summary of the methodology.

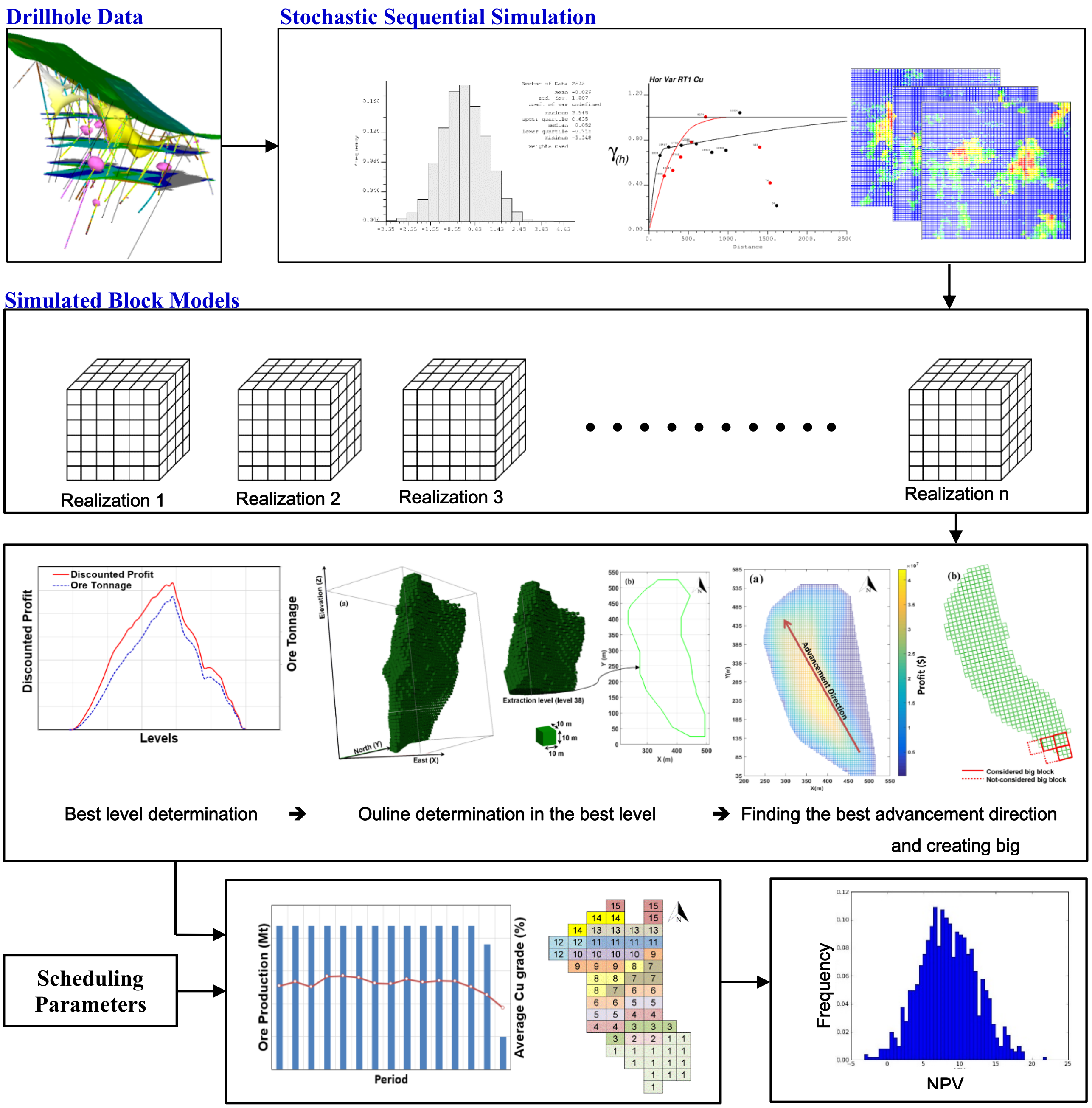


Fig 1. Steps of the implemented methodology

Table 1. Summary of applied mathematical methodologies in block-caving production scheduling (Khodayari and Pourrahimian, 2014)

<table>
<tr><th>Author</th><th>Methodology</th><th>Model's objective(s)</th><th>Features</th></tr>
<tr><td>Song (1989)</td><td>MILP</td><td>Minimization of total mining cost</td><td rowspan="14">LP

This method has been used most extensively and it can provide a mathematically provable optimum schedule. But straight LP lacks the flexibility to directly model complex underground operations which require integer decision variables.

MILP

MILP could be used to provide a series of schedules which are marginally inferior to a provable optimum. Computational ease in solving an integer-programming problem depends on the formulation structure. It can provide a mathematically provable optimum schedule. The advantage that MILP has over simulation when used to generate sub-optimal schedules is that the gap between the MILP feasible solution and the relaxed LP solution provides a measure of solution quality. The drawback in using MILP is that it is often difficult to optimize large production systems by the branch-and-bound search method.

QP

The block caving process is non-linear, so it would not be appropriate to use linear programming for production scheduling. But solving this kind of problem could be a challenge because we must change the formulation to LP and then solve the problem. Changing creates conversion errors.</td></tr>
<tr><td>Chanda (1990)</td><td>Simulation and MIP</td><td>Minimization of the deviation in the average production grade between operating shifts</td></tr>
<tr><td>Guest et al. (2000)</td><td>LP</td><td>Maximization of NPV</td></tr>
<tr><td>Rubio (2002)</td><td>MIP</td><td>Two models: (a) maximization of NPV and (b) optimization of the mine life</td></tr>
<tr><td>Diering (2004)</td><td>NLP</td><td>Maximizing NPV for M periods and minimization of the deviation between a current draw profile and a defined target</td></tr>
<tr><td>Rubio and Diering (2004)</td><td>LP, IP, QP</td><td>Maximization of NPV, optimization of draw profile, and minimization of the gap between long- and short-term planning</td></tr>
<tr><td>Rahal et al. (2008)</td><td>MILGP</td><td>Minimizing deviation from the ideal draw profile while achieving a production target</td></tr>
<tr><td>Weintraub et al. (2008)</td><td>MIP</td><td>Maximization of profit</td></tr>
<tr><td>Smoljanovic et al. (2011)</td><td>MILP</td><td>Optimization of NPV and mining material handling system</td></tr>
<tr><td>Parkinson (2012)</td><td>IP</td><td>Finding an optimal opening sequence in an automated manner</td></tr>
<tr><td>Epstein et al. (2012)</td><td>LP, IP</td><td>Maximization of NPV</td></tr>
<tr><td>Diering (2012)</td><td>QP</td><td>Objective tonnage (to optimize the shape of the cave)</td></tr>
<tr><td>Pourrahimian et al. (2013)</td><td>MILP</td><td>Maximization of NPV</td></tr>
<tr><td>Alonso-Ayuso et al. (2014)</td><td>MILP</td><td>Maximization of NPV taking into consideration the uncertainty in copper price</td></tr>
<tr><td>Pourrahimian and Askari-Nasab (2014)</td><td>MILP</td><td>Maximization of NPV, determining the BHOD based on the optimization</td><td></td></tr>
</table>

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 modeling is performed for each rock type separately. The following steps are common for generating a geological model:

First, a declustering 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 modeling, and simple kriging is used for grade modeling. 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 best level 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).

$$Dis\ \mathrm{P}_{blL} = \sum_{l=L}^{1} \frac{\mathrm{Pr}_{bll}}{(1+i)^{d/ER}}, \quad \forall bl \tag{1}$$

$$Dis\ \mathrm{P}_{L} = \sum_{bl=1}^{BL} Dis\ \mathrm{P}_{blL} \tag{2}$$

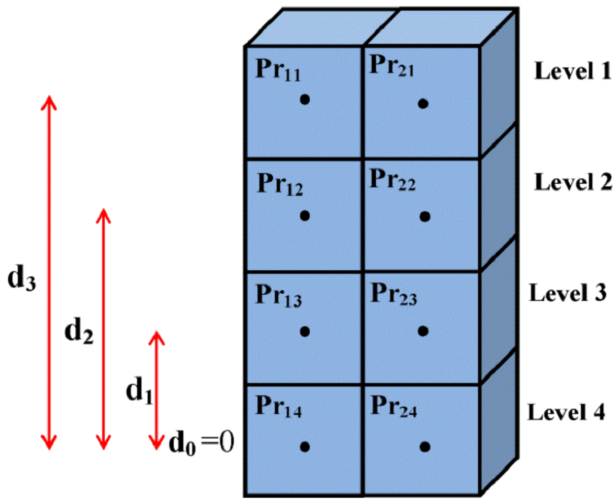
Where $Dis\ \mathrm{P}_{blL}$ is the discounted profit of ore block bl at level L; $Dis\ \mathrm{P}_{L}$ is the total discounted profit of level L, which is the summation of discounted profit of all the blocks in that level; Pr_{bll} is the profit (undiscounted) of ore block bl at level l; i is the discount rate; d is the distance between the center points of ore block bl at level L and the ore blocks above it; ER is the extraction rate per period; BL is the total number of ore blocks in level L. The profit of each ore block is calculated using the following equations:

$$T_R = g \times Ton \times R \times (P - S_C) \tag{3}$$

$$T_C = Ton \times (M_C + P_C) \tag{4}$$

$$P = T_R - T_C \tag{5}$$

Where T_R is the total revenue; R is the processing plant recovery; P is the price per ton of the product; S_C is the selling cost per ton of material; g is the element grade; T_C is the total cost; P_C is the processing plant cost and M_C is the cost of mining per ton of material. Fig 2 clearly shows how to calculate the discounted profit of a block at a given level. In Fig 2, two blocks are assumed to be in each level. Afterwards, the tonnage-profit curve is plotted and the level with the highest profit is selected for starting the extraction (Fig 3).



$$\left.\begin{aligned} Dis\,\mathrm{P}_{14} &= \frac{\mathrm{Pr}_{14}}{(1+i)^{d_0/ER}} + \frac{\mathrm{Pr}_{13}}{(1+i)^{d_1/ER}} + \frac{\mathrm{Pr}_{12}}{(1+i)^{d_2/ER}} + \frac{\mathrm{Pr}_{11}}{(1+i)^{d_3/ER}} \\ Dis\,\mathrm{P}_{24} &= \frac{\mathrm{Pr}_{24}}{(1+i)^{d_0/ER}} + \frac{\mathrm{Pr}_{23}}{(1+i)^{d_1/ER}} + \frac{\mathrm{Pr}_{22}}{(1+i)^{d_2/ER}} + \frac{\mathrm{Pr}_{21}}{(1+i)^{d_3/ER}} \end{aligned}\right\} Dis\,\mathrm{P}_{Level4} = Dis\,\mathrm{P}_{14} + Dis\,\mathrm{P}_{24}$$

Fig 2. Schematic example of calculating discounted profit of ore block at a given level

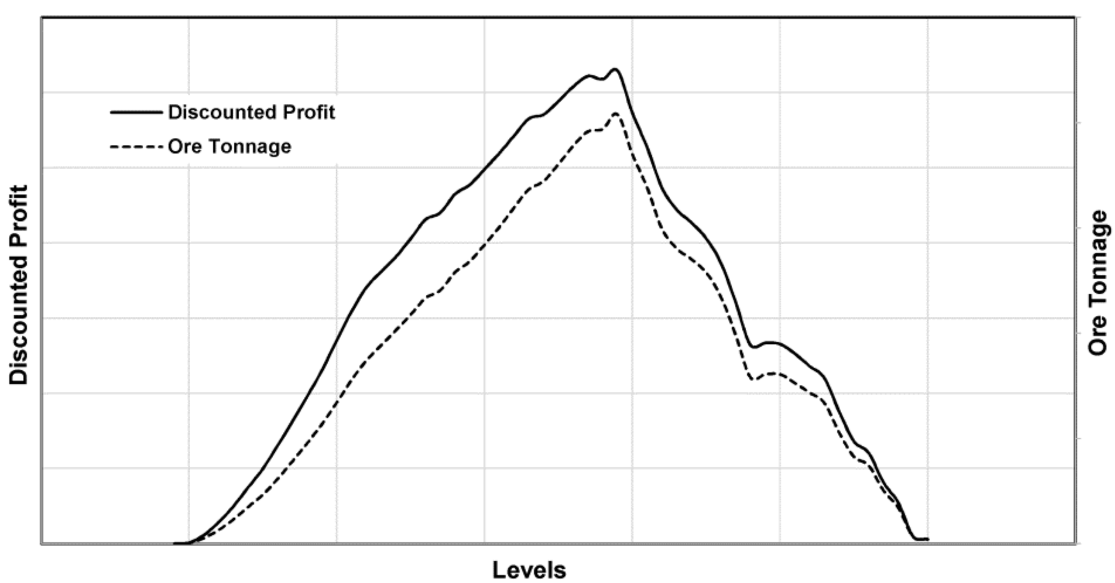


Fig 3. Schematic view of finding best level of extraction methodology

2.3. Production scheduling

After determining the best elevation, the interior of the ore-body outline in the level is divided into rectangles based on the minimum required mining footprint (see Fig 4). The minimum mining footprint (plan view) represents the minimum sized shape that will induce and sustain caving. This is similar to the hydraulic radius in a caving operation. Then all block inside of the rectangle and above that creates big-blocks. In the next step, the sequence of extraction of these big-blocks is optimized.

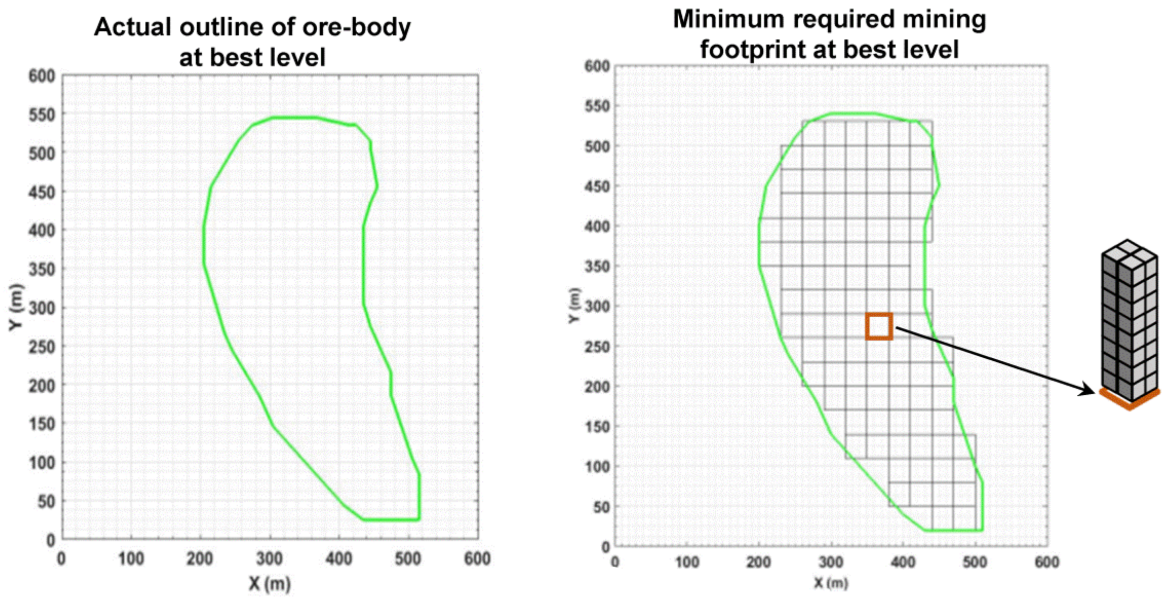


Fig 4. Schematic view of production scheduling methodology

3. Mathematical formulation

3.1. Notation

The notation of sets, indices and decision variables for the MILP model are as follows:

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 each big-block.
Ton_{bbl}	Tonnage of each big-block.
$MCL\,(Mt)$	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 acceptable average head grade of considered element.
$GU\,(\%)$	Upper bound of 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

3.2. Objective function and constraints

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. (Based on distances between drawpoints and footprint size, the ore blocks are placed into bigger blocks). The objective function, equation (6), 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.

$$Max \quad \sum_{t=1}^{T} \sum_{bbl=1}^{BBL} \frac{Profit_{bbl} \times x_{bbl,t}}{(1+i)^t} \tag{6}$$

Where $Profit_{bbl}$ is the profit value of the big-block bbl which is equal to the summation of the small ore blocks' profit within that big-block. The objective function is subject to the following constraints:

Mining capacity

$$MCL_t \le \sum_{bbl=1}^{BBL} Ton_{bbl} \times x_{bbl,t} \le MCU_t\,, \quad \forall t \in \{1,....,T\} \tag{7}$$

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.

Grade blending

$$GL_t \le \frac{\sum_{bbl=1}^{BBL} g_{bbl} \times Ton_{bbl} \times x_{bbl,t}}{\sum_{bbl=1}^{BBL} Ton_{bbl} \times x_{bbl,t}} \le GU_t\,, \quad \forall t \in \{1,...,T\} \tag{8}$$

These constraints ensure that the production's average grade is in the acceptable range.

Block extraction rate and continuous extraction constraints

$$Ton_{bbl} \times x_{bbl,t} \le ExtU_{bbl,t}\,, \quad \forall bbl \in \{1,...,BBL\},\, t \in \{1,...,T\} \tag{9}$$

$$(ExtL_{bbl,t} \times B_{bbl,t}) - (Ton_{bbl} \times x_{bbl,t}) \le L \times y_{bbl,t}\,, \quad \forall bbl \in \{1,...,BBL\},\, t \in \{1,...,T\} \tag{10}$$

$$\sum_{t'=1}^{t} x_{bbl,t'} \ge y_{bbl,t}\,, \quad \forall bbl \in \{1,...,BBL\},\, t \in \{1,...,T\} \tag{11}$$

Equation (9) ensures that the extraction rate from each big-block per period does not exceed the maximum extraction rate. $y_{bbl,t}$ in equations (10) and (11) is a binary variable which is used to activate either equation (10) or (11). Whenever equation (10) 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 (11) 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.

Binary constraints

$$\mathrm{x}_{bbl,t} \le B_{bbl,t}\,, \quad \forall bbl \in \{1,...,BBL\},\ t \in \{1,...,T\} \tag{12}$$

$$B_{bbl,t} - B_{bbl,t+1} \le 0, \quad \forall bbl \in \{1,...,BBL\},\ t \in \{1,...,T\} \tag{13}$$

Equation (12) ensures that if the extraction of one big-block is started its binary variable should be one. Also equation (13) 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 equations (11) and (13) 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.

Number of new big-blocks constraints

$$\underline{N}_{NBBL,1} \leq \sum_{bbl=1}^{BBL} B_{bbl,1} \leq \overline{N}_{NBBL,1} \ , \quad t=1 \tag{14}$$

$$\underline{N}_{NBBL,t} \leq \sum_{bbl=1}^{BBL} B_{bbl,t} - \sum_{bbl=1}^{BBL} B_{bbl,t-1} \leq \overline{N}_{NBBL,t} \quad , \ \forall t \in \{2,...,T\} \tag{15}$$

These two constraints 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 (14) is applied to period one and equation (15) is applied from period two to the end of the mine life.

Precedence constraints

$$n \times B_{bbl,t} \leq \sum_{k=0}^{n} B_{S^{bbl}(k),t} \quad , \quad \forall bbl \in \{1,...,BBL\}, \ t \in \{1,...,T\} \tag{16}$$

These constraints ensure that all the predecessor big-blocks of a given big-block bbl have been started prior to extracting this big-block.

To apply this constraint, first the adjacent big-blocks of each big-block are determined and then an advancement direction is defined. Afterwards, a perpendicular line to the advancement direction is imagined at the center point of the considered big-block. Then we have to find a point on the perpendicular line using equation (17). The coordinate of this point is (X_{new}, Y_{new}).

$$Y_{new} - y_{bbl} = -\frac{1}{m}(X_{new} - x_{bbl}) \tag{17}$$

Where m is the slope of the advancement direction; y_{bbl} and x_{bbl} are the coordinates of the considered big-block in the extraction level; X_{new} is an arbitrary coordinate and as a result, Y_{new} is calculated by equation (17). Then, using equation (18), the value of D is calculated for each adjacent big-block.

$$D = (x_{adj} - x_{bbl})(Y_{new} - y_{bbl}) - (y_{adj} - y_{bbl})(X_{new} - x_{bbl}) \tag{18}$$

Where x_{adj} and y_{adj} are the coordinates of the adjacent big-blocks of each big-block. By calculating D, if the mining direction points to the direction that y increases, big-blocks with $D < 0$ are below the perpendicular line and considered as the predecessors of a given big-block and if not, big-blocks with $D > 0$ are considered as predecessors of the specified big-block. The following example contributes significantly to a clear understanding of the methodology used for precedence constraint.

Fig 5 shows how to select the predecessors for different advancement directions. A big-block (red block) is considered and its adjacent big-blocks are BL1-BL8. In Fig 5, the blue arrow shows the advancement direction and the orange line is the imaginary perpendicular line at the center of the considered big-block. The related calculation has been summarized in Table 2. According to Fig 5a, the advancement direction is from SW to NE which means y is increasing; therefore the extraction of the big-blocks with the negative value of D should be started before the considered block. Fig 5b and Fig 5c are examples of positive values with similar directions. Big-blocks 4, 6, 7, and 8 and 6, 7, and 8 are predecessor big-blocks for red block in Fig 5b and Fig 5c respectively, as they have positive D. Also, in Fig 5d, as the advancement direction is from E to W and D should be negative, big-blocks 3, 5, and 8 that have negative D are chosen as the predecessors.

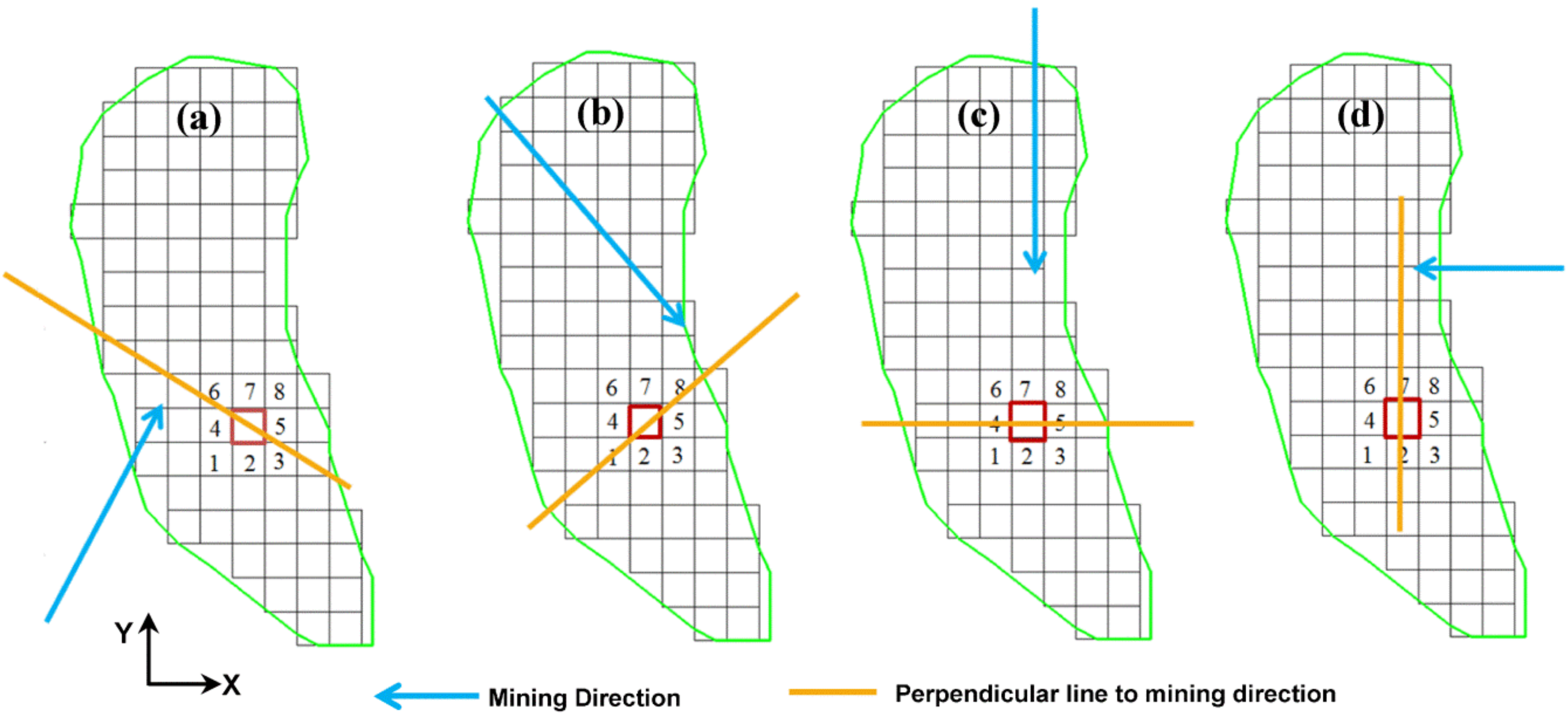


Fig 5. Schematic examples of methodology used in precedence constraint

Table 2. Example of calculation to find the predecessors of a big-block in the considered advancement direction (Fig 5a)

Direction: SW → NE
Slope of advancement direction: m = 1.8

Considered block's coordinates: (395,215)
$X_{new} = 200$

Adjacent blocks	1	2	3	4	5	6	7	8
Coordinates	(365,185)	(395,185)	(425,185)	(365,215)	(425,215)	(365,245)	(395,245)	(425,245)
D (Eq. (18))	< 0	< 0	< 0	< 0	> 0	> 0	> 0	> 0
predecessor	Yes	Yes	Yes	Yes	No	No	No	No

Reserve constraints

$$\sum_{t=1}^{T} x_{bbl,t} = 1, \quad \forall bbl \in \{1,...,BBL\} \tag{19}$$

In this formulation, all material inside of the big-blocks should be extracted. This is controlled by equation (19).

4. Solving the optimization problem

The proposed MILP model has been developed in MATLAB (Math Works Inc., 2015), 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. Authors have used the gap tolerance (EPGAP) of 1% 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

5.1. Grade uncertainty

A geostatistical study based on the drillhole data of a copper deposit and according to what is mentioned in section 2.1 was performed. Geostatistical software library (GSLIB) (Deutsch and Journel, 1998) was used for geostatistical modeling in this paper. The data belongs to the copper grade, so it is univariate data; this means there is no need for multivariate statistical analysis and transferring data to multivariate Gaussian framework to find the correlation between the variables. The initial inspection of the locations of the drillholes showed that the drillholes were equally spaced. As a result, the declustering algorithm was not implemented.

There were two parts to the modeling: rock type modeling and grade modeling. The grade modeling was implemented for both rock types (ore and waste) separately.

5.1.1. 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 6 top left shows the plan view of 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 an SIS algorithm. Plan view of rock type simulation for first realization at Elevation 40 is shown in Fig 6 (top right).

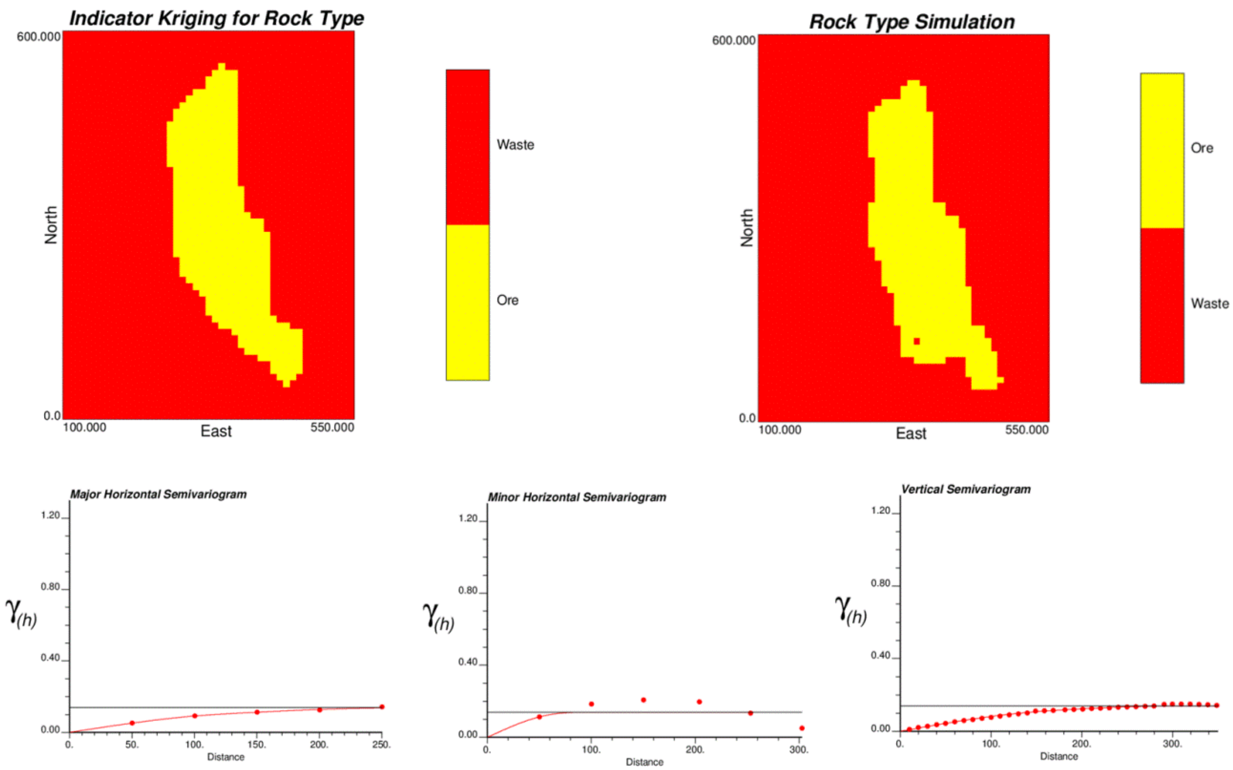


Fig 6. Rock type modeling and simulation

5.1.2. Grade Modeling

For ore modeling, 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 7 top left shows plan view of maximum direction of continuity for copper grade at Elevation 40. Traditional variogram calculation and modeling with three structures and a nugget effect of 0.1 were 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 first realization at Elevation 40 is shown in Fig 7 top right.

5.1.3. Merging grade models into rock type models

The next step was to match and merge the rock type model with the grade model for each realization. Fig 8 shows the plan view of the final simulation for the first realization. Fig 9 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.

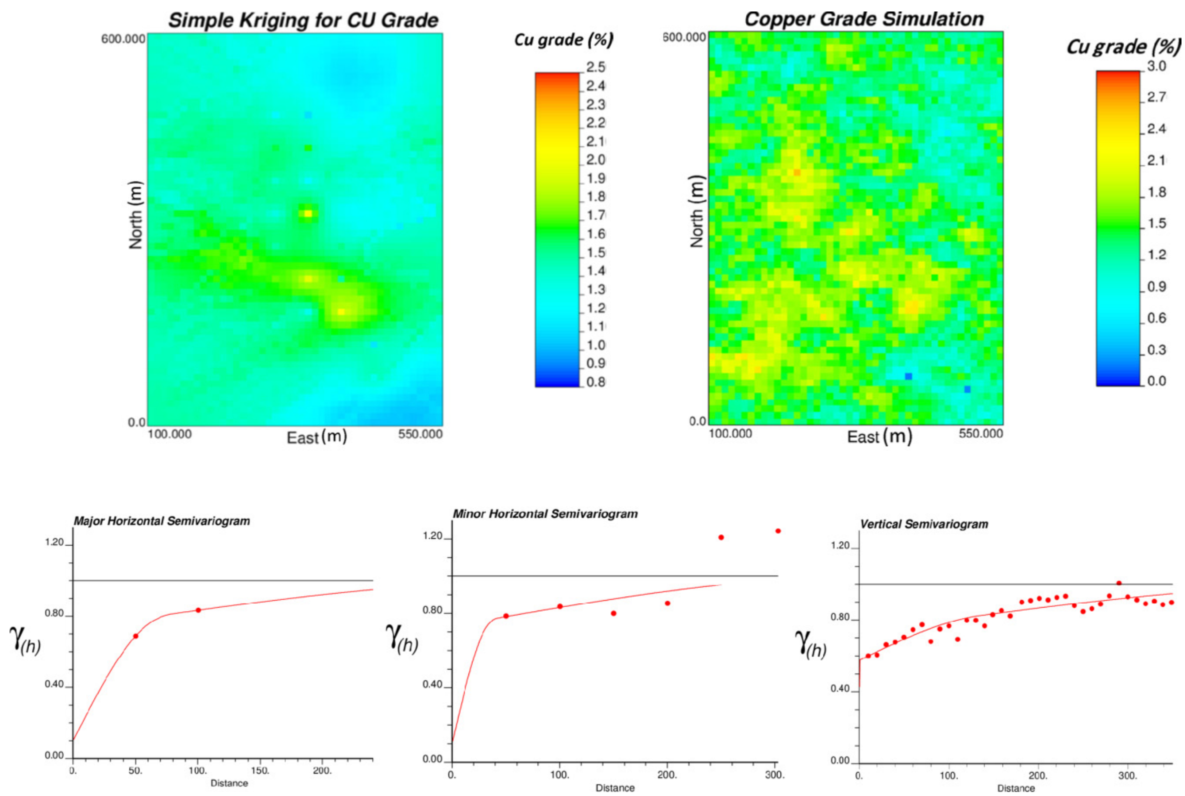


Fig 7. Grade modeling and simulation

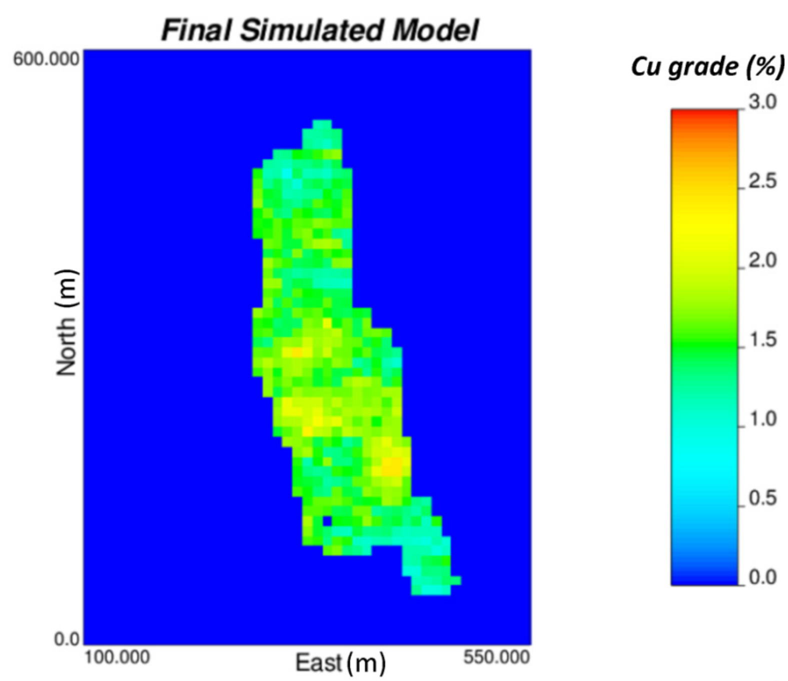


Fig 8. Final simulation of first realization at Elevation 40

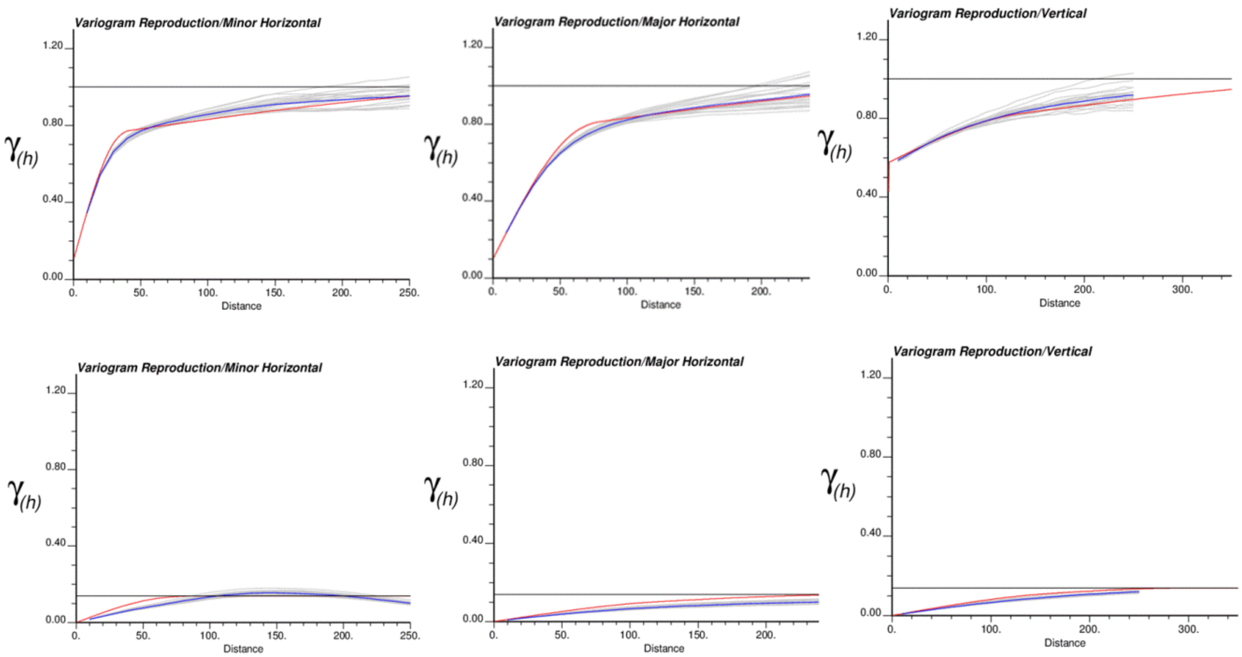


Fig 9. Variogram reproduction at Gaussian units of copper grade (top) and rock-type (bottom) realizations (gray lines), the reference variogram model (red line), and the average variogram from realizations (blue line) in three directions.

5.2. Placement of extraction level

The discounted profit and tonnage of the ore blocks above each ore block in each level were calculated and the profit-tonnage curve was plotted. The input parameters for calculating discounted profit as mentioned in section 2.2 are block height and extraction rate which were assumed to be 10 meters and 15 (meter/period) respectively. This led to selecting the best level for starting extraction based on maximum profit for each realization.

Fig 10a and 10b illustrate the best level of extraction for average simulated and original block models, respectively. Fig 10c shows the histogram of the obtained extraction levels for realizations, in 40 % of the realizations, level 39 is the best level of extraction.

To investigate the effect of the grade uncertainty, the presented MILP model should be applied on all the simulated block models. Then the NPVs of all simulated- , average simulated-, and original block model are compared. To create the average-simulated block model, the average grade of all the block models for each cell was calculated to consider one block model instead of all the block models and then the best level of extraction was found for the created average block model.

5.3. Production Scheduling

To maximize the NPV, the proposed mathematical model was applied to generate the production schedule for the level 39 of the all block models.

The ore blocks layout for level 39 was determined (e.g.Fig 11b). Then based on the method presented by Khodayari and Pourrahimian (2015) the best advancement direction for level 39 was determined (see Fig 12a) . Afterwards, because of the distances between drawpoints and the assumed footprint size (30m × 30m), 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 (see Fig 12b).

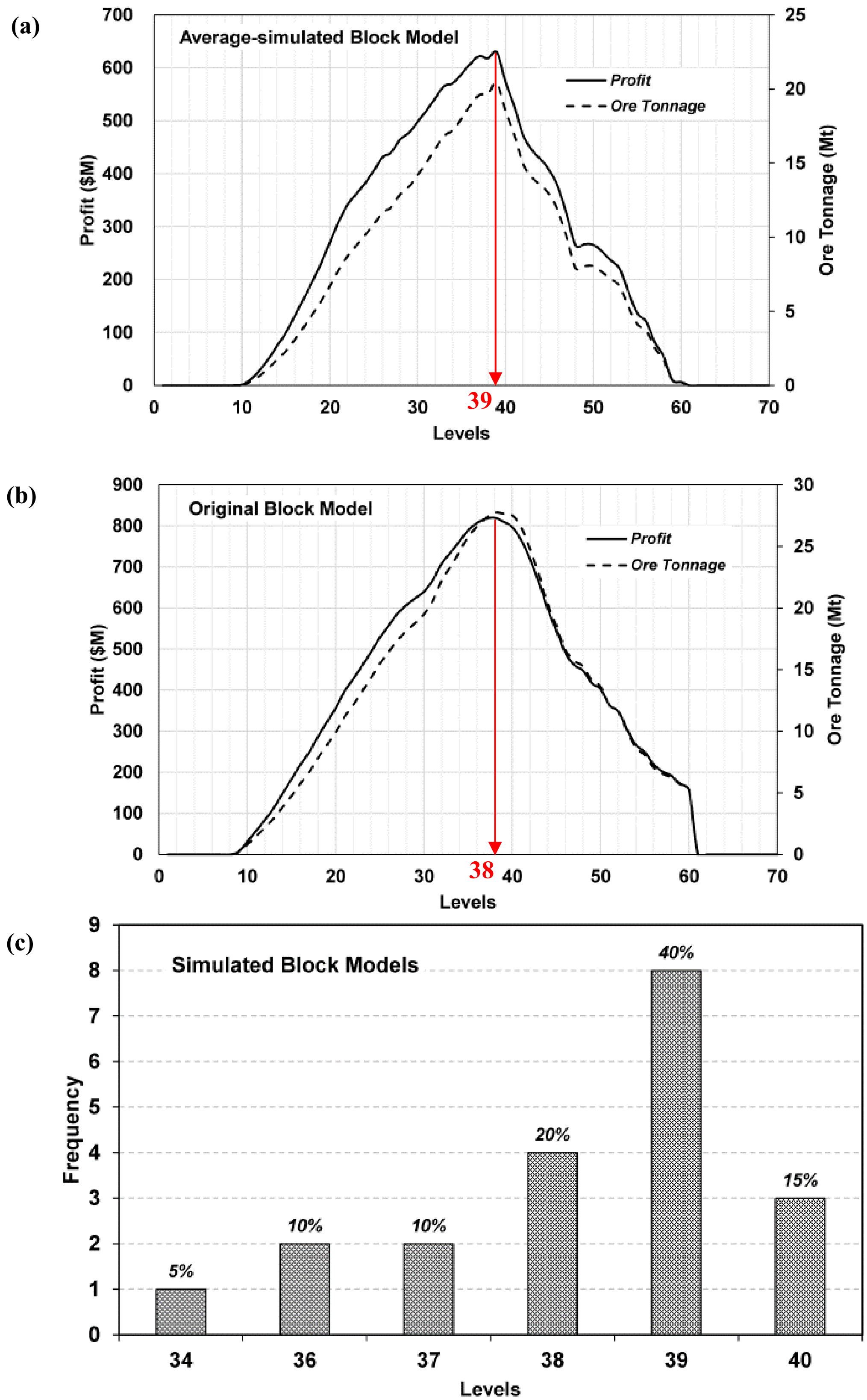


Fig 10. (a) Best level selection based on tonnage-profit curve of average-simulated block model, (b) best level selection based on tonnage-profit curve of original block model, (c) histogram of best level of extraction for simulations

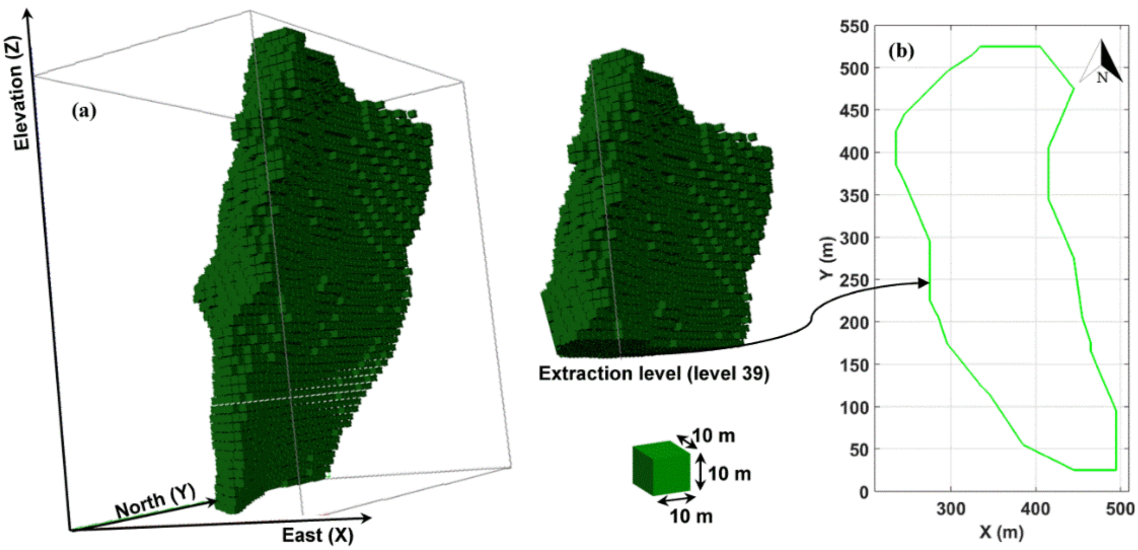


Fig 11. (a) Block model of ore-body, (b) outline of ore-body at level 39

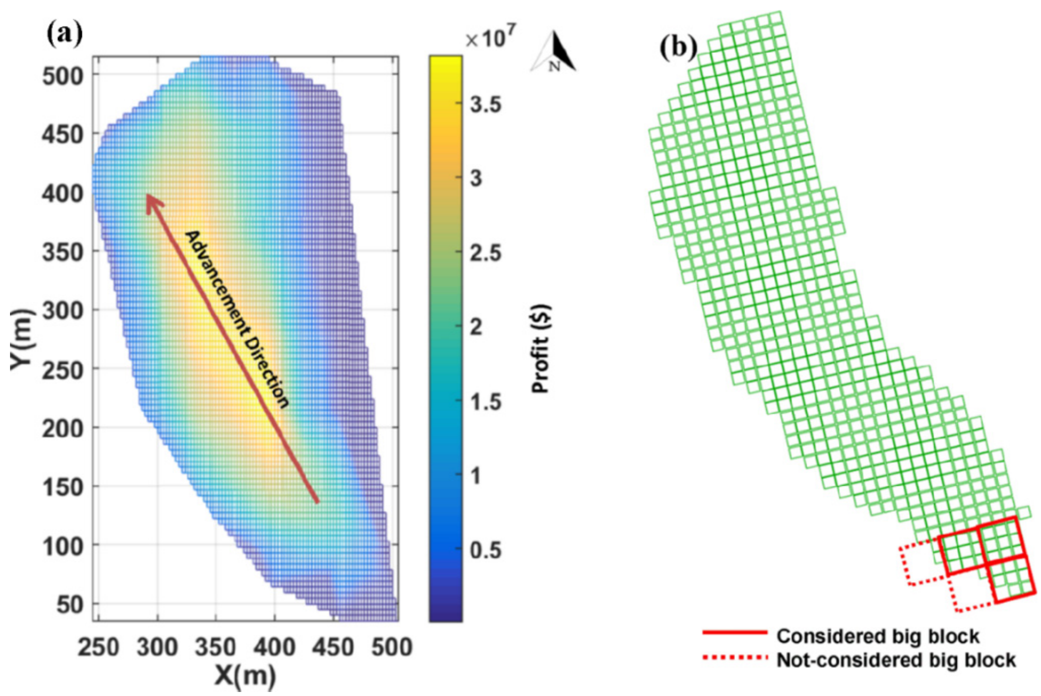


Fig 12. (a) Best advancement Direction based on the profit at the best level, (b) Schematic view of considering big-blocks with more than seven small blocks

A big-block contains seven, eight, or nine small ore blocks and all the small ore blocks above the big-block in the extraction level. Afterwards, the average grade of new big-blocks column was calculated using a weighted average method. Also, the total ore tonnage and profit values of each big-block column were calculated. After the big-block columns were created, the optimal production schedule was generated for the columns. The objective was to maximize the NPV. Table 3 shows the scheduling parameters to generate the production schedule. The coefficient matrices were created in MATLAB (Math Works Inc., 2015). CPLEX (IBM, 2015) was used to solve the problem. The model was run for level 39 on original block model with 91 big-block columns over 15 periods.

Table 3. Scheduling parameters

Parameter	Value	Parameter	Value
T	15	$P\,(\$/tonne)$	6,000
$MCL\ (Mt)$	1.2	$SC\,(\$/tonne)$	0.5
$MCU\ (Mt)$	3	$MC\,(\$/tonne)$	10
$GL\,(\%)$	1.3	$PC\,(\$/tonne)$	16.1
$GU\,(\%)$	1.6	$\overline{N}_{NBBL,1}$	27
$ExtL\ (Mt)$	0.09	$\underline{N}_{NBBL,1}$	0
$ExtU\,(Mt)$	0.35	$\overline{N}_{NBBL,t}$	5
$\mathrm{i}\,(\%)$	10	$\underline{N}_{NBBL,t}$	2
$R\,(\%)$	85		

The amount of extracted ore was 39 Mt with the NPV of $1.036 B. Fig 13 shows the production average grade and production tonnage in each period for this level. As it can be seen from the production graph, the maximum amount of material has been extracted in early periods and for the rest of the mine life it has been decreased gradually. Also in the grade graph, it has been increased slowly in early periods and the material with higher grades were extracted at first, then it starts decreasing near the end of the mine life. Fig 14 shows the number of active and new big-blocks in which the number of new big-blocks are within the defined range. The formulation tries to open more big-blocks at the first period in order to maximize the NPV and because of that 25 big-blocks were opened at period one. Moreover, the precedence of extraction is shown in Fig 15.

The tonnage and NPV changes for all the realizations and original block model at level 39 were examined. Fig 16 illustrates the frequency of NPV at level 39 for all the realizations. As it can be seen, the NPV varies between $0.96 B and $1.08 B. Fig 17 shows the tonnage analysis, the ore tonnage changes between 33.1 Mt and 39.6 Mt and for the original block model it stands above the average.

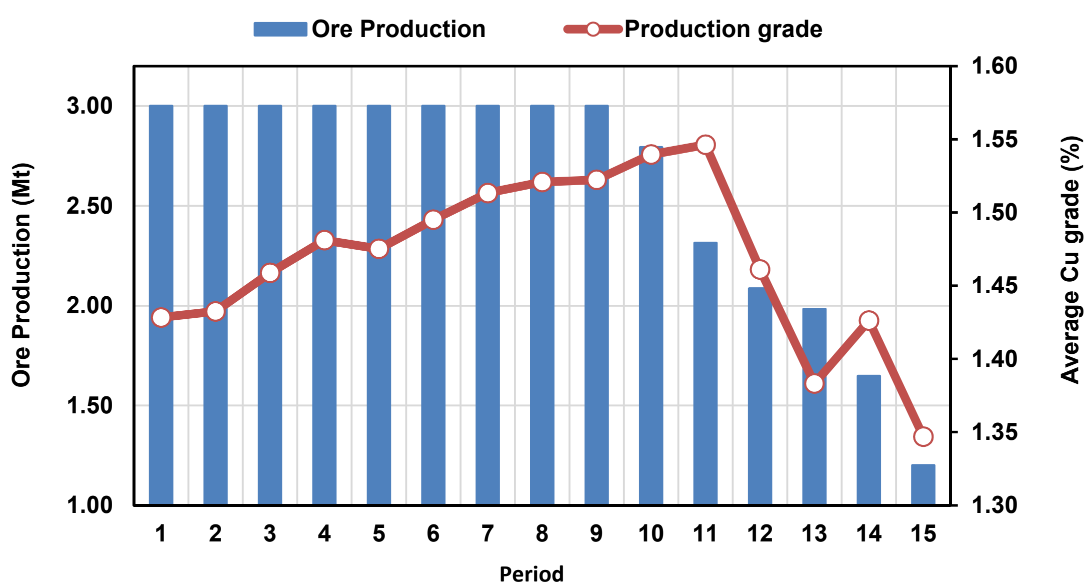


Fig 13. Production tonnage and average grade of production at level 39

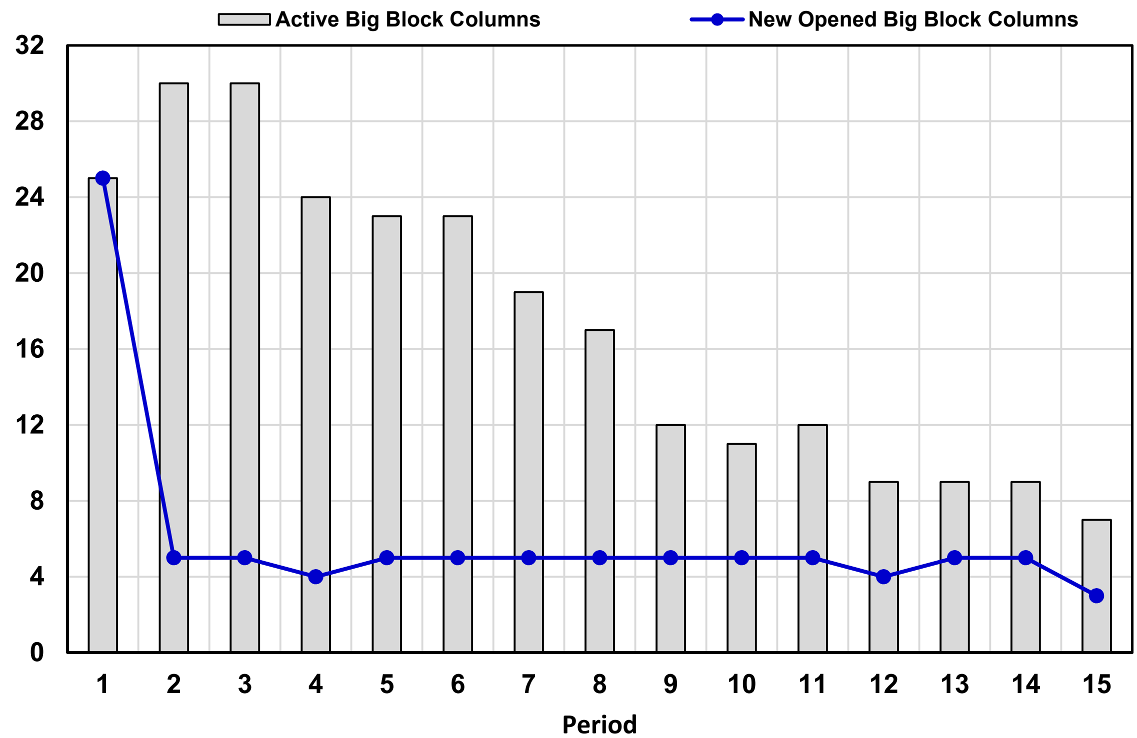


Fig 14. Number of active and new big-blocks for each period at level 39

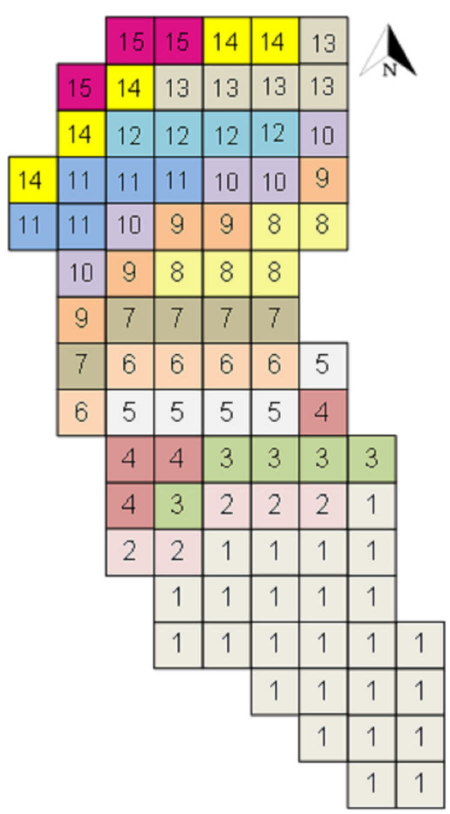


Fig 15. Starting extraction period of big-blocks at level 39 (numbers represent the starting period)

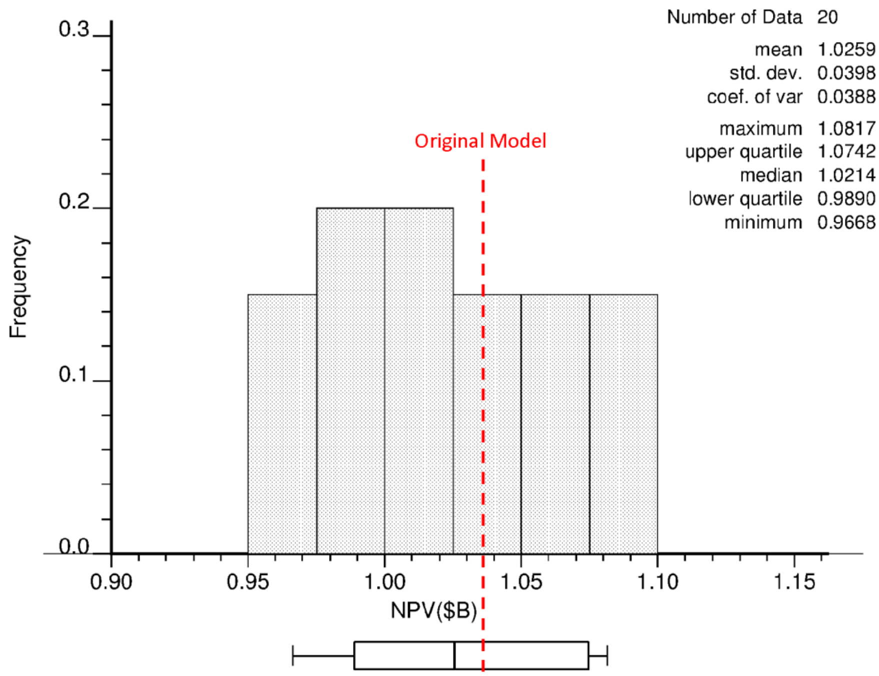


Fig 16. The NPV frequency for all the realizations at level 39

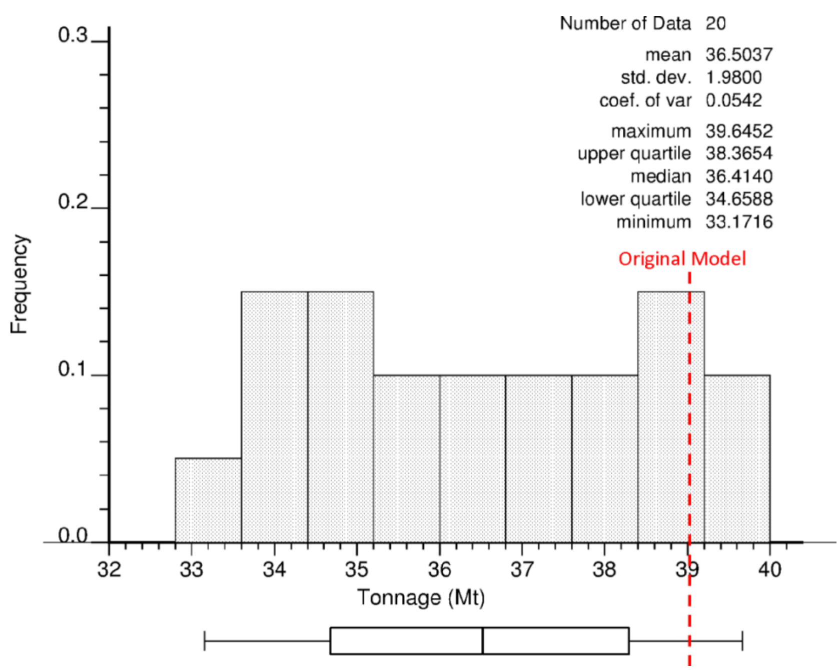


Fig 17. The tonnage frequency for all the realizations at level 39

6. Conclusion

Geological uncertainty has been used in open-pit mining, but is less studied in underground mining, especially in block caving, where it is not so easy to revise production plans after caving has begun. The methodology used in this paper is able to find the best extraction horizon placement under grade uncertainty. Also, it is able to define an optimal production scheduling using mathematical programming and MILP formulation in MATLAB and solving it using CPLEX.

Optimizing one block model (original or average-simulated) will result in a single number. But when a number of block models are optimized, the obtained results show a range associated with the risk of project.

The results from the NPV analysis showed that the difference between the NPV of original block model and the minimum value was 7.15% and the difference from the maximum value was 4.41%. Following the same manner for tonnage, those differences from minimum and maximum values were 17.63% and 1.6%, respectively.

7. References

[1] Albor, F. and Dimitrakopoulos, R. (2009). Stochastic mine design optimization based on simulated annealing: pit limits, production schedules, multiple orebody scebarios and sensitivity analysis. *IMM Transactions Mining Technology*, *118* (2), 80-91.

[2] Alonso-Ayuso, A., Carvallo, F., Escudero, L. F., Guignard, M., Pi, J., Puranmalka, R., and Weintraub, A. (2014). Medium range optimization of copper extraction planning under uncertainty in future copper prices. *European Journal of Operational Research*, *233* (3), 711-726.

[3] Asad, M. W. A. and Dimitrakopoulos, R. (2013). Implementing a parametric maximum flow algorithm for optimal open pit mine design under uncertain supply and demand. *Journal of the Operational Research Society*, *64* (2), 185-197.

[4] Carpentier, S., Gamache, M., and Dimitrakopoulos, R. (2016). Underground long-term mine production scheduling with integrated geological risk management. *Mining Technology*, *125* (2), 93-102.

[5] Chanda, E. C. K. (1990). An application of integer programming and simulation to production planning for a stratiform ore body. *Mining Science and Technology*, *11* (2), 165-172.

[6] Deutsch, C. V. and Journel, A. G. (1998). *GSLIB : geostatistical software library and user's guide.* Vol. 2, Oxford University Press, New York,369.

[7] Diering, T. (2004). *Computational considerations for production scheduling of block cave mines*. in Proceedings of MassMin 2004, Santiago, Chile, pp. 135-140.

[8] Diering, T. (2012). Quadratic Programming applications to block cave scheduling and cave management. in *Massmin 2012*. Sudbury, Canada, pp. 1-8.

[9] Diering, T., Richter, O., and Villa, D. (2008). Block cave production scheduling using PCBC. in *MassMin 2008*. Luleå, Sweden.

[10] Dimitrakopoulos, R. and Ramazan, S. (2008). Stochastic integer programming for optimising long term production schedules of open pit mines: methods, application and value of stochastic solutions. *Mining Technology*, *117* (4), 155-160.

[11] Dowd, P. A. (1994). Risk assessment in reserve estimation and open-pit planning. *Trans. Instn. Min. Metall.*, *103* A148 - A154.

[12] Epstein, R., Goic, M., Weintraub, A., Catalán, J., Santibáñez, P., Urrutia, R., Cancino, R., Gaete, S., Aguayo, A., and Caro, F. (2012). Optimizing Long-Term Production Plans in Underground and Open-Pit Copper Mines. *Operations Research*, *60* (1), 4-17.

[13] Grieco, N. and Dimitrakopoulos, R. (2007). Managing grade risk stope design optimisation: Probabilistic mathematical programming model and application in sublevel stoping. *IMM Transactions Mining Technology*, *116* (2), 49-57.

[14] Guest, A. R., Van Hout, G. J., and Von Johannides, A. (2000). *An Application of Linear Programming for Block Cave Draw Control*. in Proceedings of MassMin, The Australasian Institute of Mining and Metallurgy, Brisbane, Australia, pp. 461-468.

[15] IBM (2015). IBM ILOG CPLEX 12.6.2. Ver.

[16] Khodayari, F. and Pourrahimian, Y. (2014). Determination of the best height of draw in block cave sequence optimization. in *Mass Min 2014*. Santiago, Chile, pp. 457-465.

[17] Khodayari, F. and Pourrahimian, Y. (2015). Determination of development precedence for drawpoints in block-cave mining. in *5th International Symposium Mineral Resources and Mine Development (AIMS 2015)* Aachen, Germany, pp. 383-391.

[18] Koushavand, B. and Askari-Nasab, H. (2009). Transfer of Geological Uncertainty into Mine Planning. in *Mine Planning and Equipment Selection (MPES) CD-ROM*. Banff, Alberta, Canada, pp. 462-476.

[19] Lamghari, A. and Dimitrakopoulos, R. (2012). A diversified Tabu search approach for open-pit mine production scheduling problem with metal uncertainty. *European Journal of Operational Research*, *222* (3), 642-652.

[20] Lamghari, A., Dimitrakopoulos, R., and Ferland, J. (2013). A variable neighbourhood decent algorithm for the open-pit mine production scheduling problem with metal uncertainty *Journal of the Operational Research Society 65* (9), 1305-1314.

[21] Leite, A. and Dimitrakopoulos, R. (2007). Stochastic optimization model for open-pit mine planning: application and risk analysis at a copper deposit. *IMM Transactions Mining Technology*, *116* (3), 109-118.

[22] Lerchs, H. and Grossmann, I. (1965). Optimum design of open-pit mines. *Canadian Mining Metallurgical Bull*, *58* 17-24.

[23] Maleki, M. and Emery, X. (2015). Joint simulation of grade and rock type in a stratabound copper deposit *Mathematical Geosciences 47* (4), 471-495.

[24] Montiel, L., Dimitrakopoulos, R., and Kawahata, K. (2015). Globally optimising open-pit and underground mining operations under geological uncertainty. *Mining Technology*, *00* (0), 1-13.

[25] Osanloo, M., Gholamnejad, J., and Karimi, B. (2008). Long-term open pit mine production planning: a review of models and algorithms. *International Journal of Mining, Reclamation and Environment*, *22* (1), 3-35.

[26] Parkinson, A. (2012). Essays on Sequence Optimization in Block Cave Mining and Inventory Policies with Two Delivery Sizes.Thesis, The University Of British Columbia, The University Of British Columbia, Pages 199.

[27] Pourrahimian, Y. and Askari-Nasab, H. (2014). An application of mathematical programming to determine the best height of draw in block-cave sequence optimization. *Mining Technology (Trans. Inst. Min. Metall. A)*, *123* (3), 162-172.

[28] Pourrahimian, Y., Askari-Nasab, H., and Tannant, D. (2013). A multi-step approach for block-cave production scheduling optimization. *International Journal of Mining Science and Technology*, *23* (5), 739-750.

[29] Rahal, D., Dudley, J., and Hout, G. v. (2008). *Developing an optimised production forecast at Northparkes E48 mine using MILP*. in Proceedings of 5th International Conference and Exhibition on Mass Mining, Luleå Sweden, pp. 227-236.

[30] Ramazan, S. and Dimitrakopoulos, R. (2004). Traditional and New MIP Models for Production Scheduling With In-Situ Grade Variability. *International Journal of Surface Mining, Reclamation and Environment*, *18* (2), 85-98.

[31] Ramazan, S. and Dimitrakopoulos, R. (2013). Production scheduling with uncertain supply: a new solution to the open-pit mining problem *Optimization and Engineering*, *14* (2), 361-380.

[32] Ravenscroft, P. (1992). Risk analysis for mine scheduling by conditional simulation. *Canadian Mining and Metallurgical Bulletin*,

[33] Rubio, E. (2002). Long term planning of block caving operations using mathematical programming tools.Thesis, The University of British Columbia, Pages 126.

[34] Rubio, E. and Diering, T. (2004). *block cave production planning using operation research tool*. in Proceedings of Massmin 2004, Gemcom, Santiago, Chile, pp. 141-149.

[35] Sabour, S. A. and Dimitrakopoulos, R. (2011). Incorporating geological and market uncertainties and operational flexibility into open pit mine design. *Journal of Mining Science*, *47* (2), 191-201.

[36] Smoljanovic, M., Rubio, E., and Morales, N. (2011). *Panel Caving Scheduling Under Precedence Constraints Considering Mining System*. in Proceedings of 35th APCOM Symposium, Wollongong, NSW, Australia, pp. 407-417.

[37] Song, X. (1989). *Caving process simulation and optimal mining sequence at Tong Kuang Yu mine, China*. in Proceedings of pp. 386-392.

[38] Vargas, E., Morales, N., and Emery, X. (2014). *Footprint and economic envelope calculation for block/panel caving mines under geological uncertainty*. in Proceedings of Caving 2014, Santiago, Chile, pp. 449-456.

[39] Weintraub, A., Pereira, M., and Schultz, X. (2008). A Priori and A Posteriori Aggregation Procedures to Reduce Model Size in MIP Mine Planning Models. *Electronic Notes in Discrete Mathematics 30* 297–302.

Comparison of Recoverable Reserves between Simulation and Kriging for Block Caving with Optimized Drawpoints

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Abstract

At present, it is well known that Kriging is the most popular geostatistical estimation technique in the mining industry. However, Sequential Gaussian Simulation keeps gaining more terrain in this important extractive industry. For instance, realizations have being used in different mining applications to solve specific issues for the operation, planning, and design of the mining projects. A potential field where simulation can be explored is the design for block caving, so that reliable results of minable resource is obtained. In the block caving, the constraints and parameters are numerous and the calculation of recoverable reserves tend to be very challenging. Nonetheless, this paper suggests a short guide to manage the Kriging and simulation block models generated by GSLIB and to process them into Gems-PCBC. The response results of tonnage, grade and profit based on the both techniques have been compared, and an interesting discussion about SGS advantages is given. The possible impacts that these results might cause in the economics of a block caving mines is also discussed. Regardless certain drawbacks, the methodology based on sequential Gaussian simulation to obtain the recoverable reserves is suggested.

1. Introduction

There are many detailed studies contrasting kriging and simulation for estimating recoverable resources and reserves. Nonetheless, the intention of this paper is not to repeat all that so far has been reviewed about these two types of techniques, neither to show in this document an underground mining approach related to block caving; that would be more extensive and more oriented to mining engineering. This paper basically explains the final results of the optimal minable reserves obtained within a commercial software by using previous numerical models generated with kriging and simulation, and the overall impact that these models could cause to the economics and to the evaluation of a block-caving project.

The beginning of the paper is dedicated to explain briefly about simulation and kriging, where certain studies regarding these geostatistical techniques are highlighted. The second part of this

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paper recommends a number of geostatistical programs that are used to perform block models, from the GSLIB catalog's software (Deutsch, C. V., & Journel, 1998) as well as the PCBC (Gems, Dassault Systemes) that is used to process these numerical models, so that the optimized recoverable resources can be calculated. Before the numerical models are processed, they first have to be imported into a commercial software specialized for block caving (PCBC-Gems). The last part of the paper includes a short explanation to obtain recoverable reserves by "all realizations all the time"; therefore, all the results obtained from all realizations are contrasted with the results given by ordinary kriging in terms of net value, tonnage, and grade. Figures and snapshots with setting of the mining parameters and runs, as well as, tables and plots with results are shown in this paper.

2. Simulation and Kriging

There are a good number of papers and theses that have been written about both kriging and simulation over the past years; these works include differences, advantages and disadvantages. For instance, the short paper wrote by B. Wilde and C. Deutsch in the CCG report, 2005, titled “the Comparison of Kriging and the Average of Simulated Realizations” is one of them. This interesting note shows several examples where the authors mention that “it is incorrect to assume that ordinary kriging is the same as the average of simulated realizations”. Another interesting work is the study made by Deepak Bhandari, 2007, “Comparison of Recoverable Reserves Estimation Techniques”; his theses to obtain a Master of Science at University of Alberta. In his theses, Deepak performed a comparison of estimated values to reference values for kriging and SGS. He concluded that simulation removes the smoothing of grade that kriging usually generate, thus SGS has the capability of producing very high and very low values providing a very solid platform for decision making. Deepak, however, mentioned in his work that SGS possesses a small disadvantage that is related to the management of multiple realizations. This drawback used to make the mine design and planning more challenging. However, recent computational developments allow to improve the management of a reasonable number of realizations.

Many studies confirm that kriging is very popular and is referred to as “the Best Linear Unbiased Estimate”; this geostatistical technique is being used for decades in the mining industry despite the smoothing effect on grades (Cu) that it can be generated. In contrast, a great number of studies and research show that simulation is being used a lot and for many years on the hydrocarbon reservoir modeling, yet lesser in mining. Nonetheless, mining professionals have been given much more attention to this technique, thus SGS is gaining more space in this sector.

The main advantage of the simulated realizations is that they allow performing good uncertainty assessments. Furthermore, it is important to mention that advances in computational hardware, software, and intense research on simulation applications is making the use of this geostatistical technique commonplace (Deutsch, 2015). In fact, simulation has shown that it has a good potential to be applied in the mining industry.

3. Common Programs to Obtain Recoverable Resources

Here is listed the main programs that are used to obtain the kriged and simulated block models, so that the mineral reserve calculation can be performed. In addition, a brief explanation to generate the numerical models that is imported to third party software is made. The manipulation of these numerical models is performed within PCBC-Gems, thus the estimates of recoverable reserves for the block-caving mines are obtained.

First, several steps need to be conducted to produce a kriged block model that requires the usage of some programs from the GSLIB catalog (Deutsch & Journel, 1998). This detailed guide should contain a step-by-step procedure. However, this paper only includes an overall explanation to perform a kriging estimation, as shown in Fig 1.

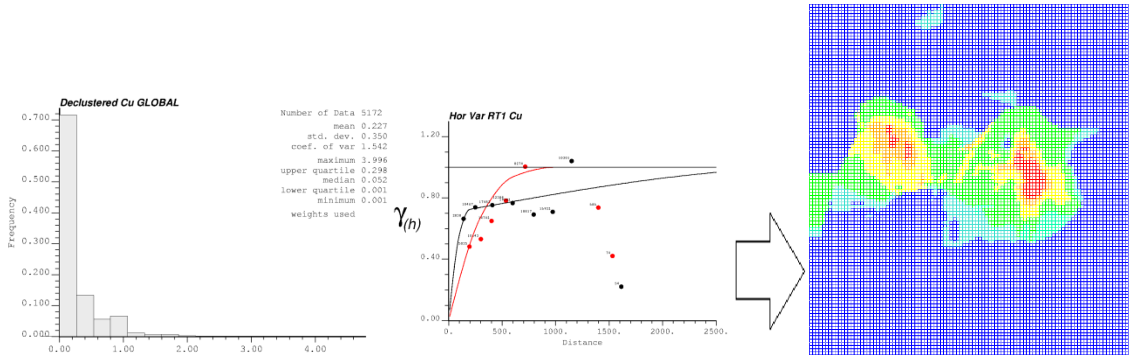


Fig 1. The generalized steps to generate a kriged block model with GSLIB programs

1. *Compositing:* This software was developed by D. S. F. Silva (2014). It calculates compositing using assay data of the format (ID FROM TO VAR1 … VARn). Notice that compositing is the starting point of any geostatistical estimation.
2. *HISTPLT:* This program has been written to generate some relevant univariate statistical summaries and show comprehensive histogram plots.
3. *GAMV:* The program is commonly used for irregularly spaced data, and the experimental semi-variogram is calculated.
4. *VMODEL:* This is a program for variogram fitting, and allow for fitting any number of variogram points with some nested spherical structures.
5. *kt3d:* The main program here is the 3-D kriging program (kt3d). This program performs kriging estimations on a grid, and also kt3d is helpful to conduct an efficient cross-validation before kriging or simulation is performed.

To create a number of conditional realizations of an input variable (Cu) and use the equally-probably numerical models in PCBC (transfer function) to yield the recoverable resources, it is necessary to replicate the steps presented by Leuangthong et al. (2004) where GSLIB programs are used. Notice that every step is linked to a specific GSLIB program. Some of them are already mentioned, above.

1. Composite data (Compositing) and generate histograms (HISTPLT) are also needed for simulation.
2. *DECLUS:* The program is used to obtain the declustering weights. This program provides an algorithm for generating 3D declustering weights for the composited data used in simulation
3. *NSCORE:* This program allows data transformation from original unit to the Gaussian units.
4. The *GAMV* and *VMODEL* are also used for simulation in order to fit an isotropic variogram with two nested spherical structures from the normal scored data.
5. *SGS:* The sequential Gaussian simulation program is one of the most commonly applied methods for simulation. This is the most important software at this section
6. *Histpltsim:* This is software for histogram reproducibility. It is important to mention that, the quality of the simulation model is checked by histogram and variogram reproducibility.

After the main GSLIB software are listed above, it worth to emphasize the step by step explanation to perform kriging and simulation is not very well detailed in this paper. The theses "Comparison of Recoverable Reserves Estimation Techniques" wrote by Deepak B. (2007) would be used as a guide. Fig 2 shows histogram, a fitted variogram and a kriging model. Declustering plot along with fitted variograms, and an example of the 40 realizations are displayed.

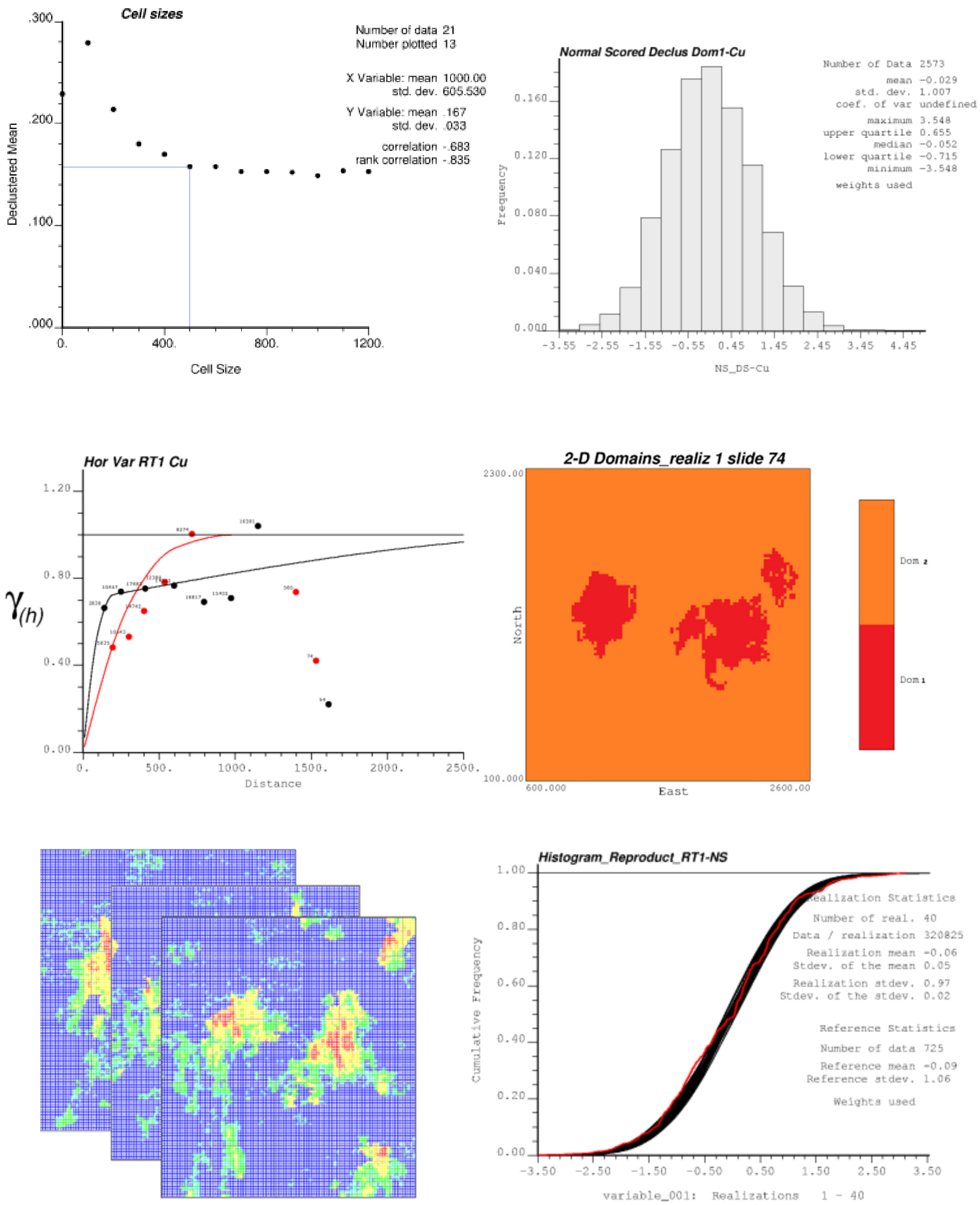


Fig 2. Main steps to generate a set of 40 realizations.

Once the kriged numerical model and the 40 realizations have been performed, they need to be imported into Gems. When each realization and kriging copper model is imported to this commercial software, each one of them is considered as an independent block model. Hence, forty-one block models are now ready to be processes within Gems-PCBC. Notice that these forty-one block models need to have lithology, density and percentage of fines before any further evaluation. These values have been previously calculated and imported to Gems, as well.

As mentioned above, Gems Software has a module called PCBC. This module is a specialized section for block caving. In PCBC, the block models, which are imported and set in Gems, are manipulated in order to perform the calculation of the recoverable reserves. Fig 3 shows two plots summarizing the PCBC routine to obtain the recoverable resources after the numerical models are imported and the layout is set. This paper does not pretend to show a complete procedure for using the PCBC module.

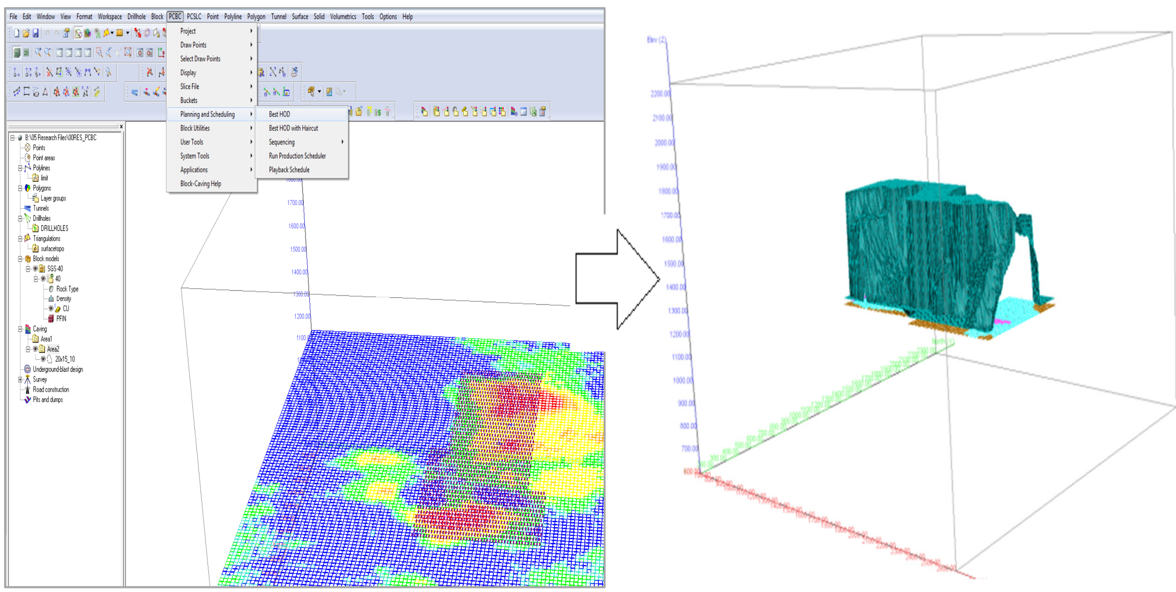


Fig 3. Summary of the PCBC work. From the imported block models through the recoverable reserves

Fig 4 shows relevant settings to generate the net value and the recoverable reserves within PCBC. These plots illustrate an overall idea about how the parameters and assumptions need to be completed inside the block-caving module of Gems.

The manipulation of these numerical models within PCBC is certainly the main part of this paper because the results that are obtained in this stage are relevant for our purpose of comparing the recoverable reserves based on Kriged block model against the recoverable reserves from the 40 realizations. Notice that the average of the 40 response values is compared to the response values of the kriged block model.

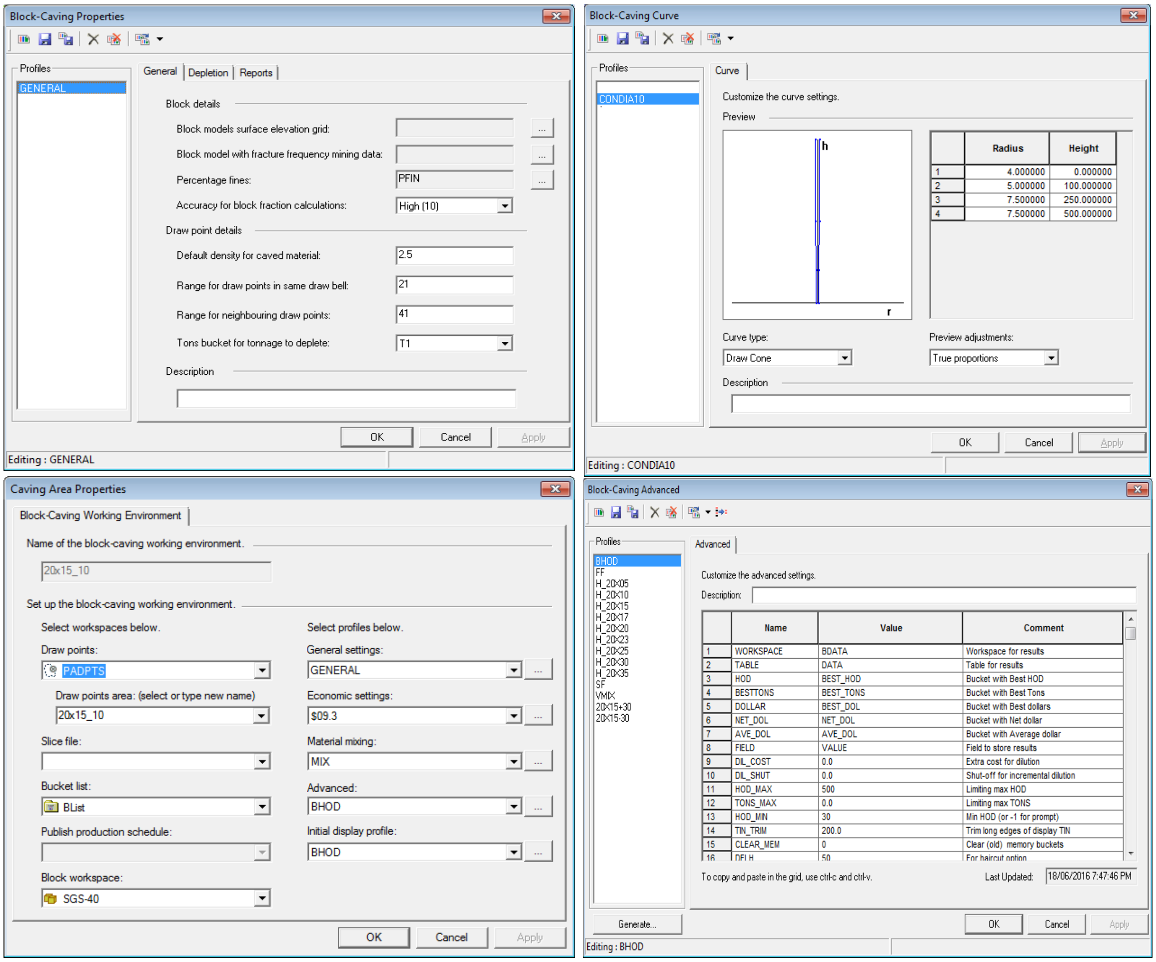


Fig 4. Snapshots of the PCBC panels with the setting to generate responses of reserves and net values

4. Compare Results from OK and SGS: Tonnage, Grade and Net Value(profit)

To compare the results of the optimized reserves, based on kriging against the results from simulation is essential to manipulate the numerical models with PCBC-Gems. Then, it is important to start choosing the layouts for the extraction level. They contain several parameters that need to be considered. A schematic plot is shown in Fig 5 where (A) is the spacing between drawpoint in a drawbell, also called brow to brow spacing, (B) is the spacing of the draw zones across minor Apex, (C) is spacing of draw zones across major Apex, (D) is the width of extraction drive and (E) is the distance between two extraction drifts (Ahmed, 2014). For the purpose of the study, a number of layouts are set in PCBC. Table 1 shows the three main layouts that are used in this work.

After the drawpoint spacing of each layout for the extraction level is set, additional block caving setting is performed in PCBC-Gems. Fig 4 shows the main panels that is filled out with assumptions and mining parameters. For instance, mining and development cost, density, percent of fines, drawcone radius, etc. Some mining assumptions can be seen in Table 2.

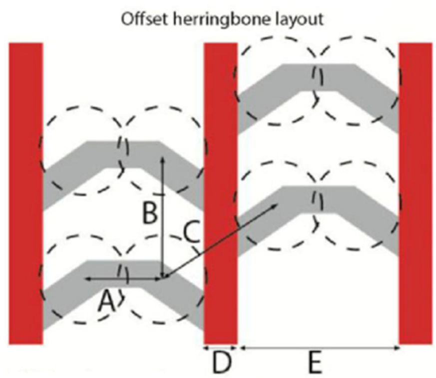


Fig 5. Scheme of the parameters of design in an extraction level (Ahmed, 2014).

Table 1. Drawpoint layouts used to find the optimal net value

Layout type (Herringbone)	Spacing across major pillar (m)	Spacing across minor pillar (m)	Observation
20x10_10	20	10	The distance between drawpoints within same bell is 10m
20x15_10	20	15	
20x20_10	20	20	

Table 2. Mining parameters and assumptions for PCBC.

Parameters & Assumptions	Value	Units	Description	References
% of Fines	30	%	Based on a model of fines	Diering, T., (2013)
Density	2.5	kg/cm^3	Average density for the orebody	Authors (2016)
HIZ	100	m	Height for interaction zone	Diering, T., (2013)
Swell factor	1.2	-	Stablished by experience	Authors (2016)
HOD_MAX	500	m	Maximum Height of Development	Diering, T., (2000)
HOD_MIN	30	m	Minimum Height of Development	Diering, T., (2000)
Discount Rate	0	%	It is assumed 0 % discount rate	Authors (2016)
Initial Elevation	1150	m	Initial Elevation of extraction	Get from Geovia info “Footprint Finder”
Draw cone radius	5	m	Based on fragment sizes	Laubscher D. (1994)
layout type	-	H	Herringbone is the layout type	Ahmed, H. et al.(2014)

The copper values of the 40 realizations as well as the copper values of the kriged model have been considered as the input variables. The Gems-PCBC is used as the transfer function of the simulation and kriging systems. The recoverable reserves and the net value are the response variables; they are in terms of tonnage and dollars respectively. In the Table 3, the tonnage results based on the simulated realizations are summarized and contrasted to the results obtained by processing the kriged block model.

For the kriged model, the maximum value of tonnage and grade are given for the extraction layout of 20×10_10 while the layout 20×15_10 shows the highest net value. In contrast, the SGS model show two scenarios. First, the mean of the 40 responses suggest that the maximum value of tonnage and grade is in the extraction layout of 20×10_10, and the highest net value is obtained from layout 20×15_10. The second scenario, shown in the Table 3, gives 40 equally probably results of the tonnage, grade and net value. Notice that the maximum possible tonnage is calculated within realization R=10 and the minimum possible tonnage is calculated within realization R=4. The results can be also used to perform further risk management, and to do decision making assessments.

The response results have been affected by the number of drawpoints, and consequently by the development cost. Fig 6 shows a plot where the averaged tonnage of the 40 realizations is contrasted with the tonnage and grade of optimized kriged model for the three chosen extraction layouts. The decrease on the tonnage is here directly related to the decrease of the number of drawpoints.

Table 3. Results of tonnage, grade and net value to compare the OK and SGS recoverable reserves

Extraction	Recoverable Reserves (Mt)			
Layout	Minimum- SGS	Maximum SGSim	Mean SGSim	Kriging
20x10_10	234 (R=40)	315 (R =10)	285	303
20x15_10	220 (R=9)	267 (R =36)	249	263
20x20_10	184 (R=4)	221 (R =7)	207	216
	Total Grade (Cu %)			
20x10_10	0.68 (R=7)	0.78(R =36)	0.72	0.72
20x15_10	0.60 (R =34)	0.69(R =36)	0.65	0.65
20x20_10	0.55 (R =3)	0.65(R =36)	0.61	0.61
	Net Value (million $)			
20x10_10	919(R =3)	1998(R =36)	1516	1650
20x15_10	1530(R =3)	2384 (R =5)	2046	2202
20x20_10	1581(R =3)	2256 (R =5)	1989	2125

Table 4 shows the layout of extraction 20×10_10 contains 4570 drawpoints. Therefore, the greatest amount of tonnage is expected to be extracted from this layout (Fig 7). However, the development cost is the highest. As a result, it causes the net value to be the lowest, among the three extraction layouts. Fig 7 also displays that the maximum net value possible is within the 20×15_10.

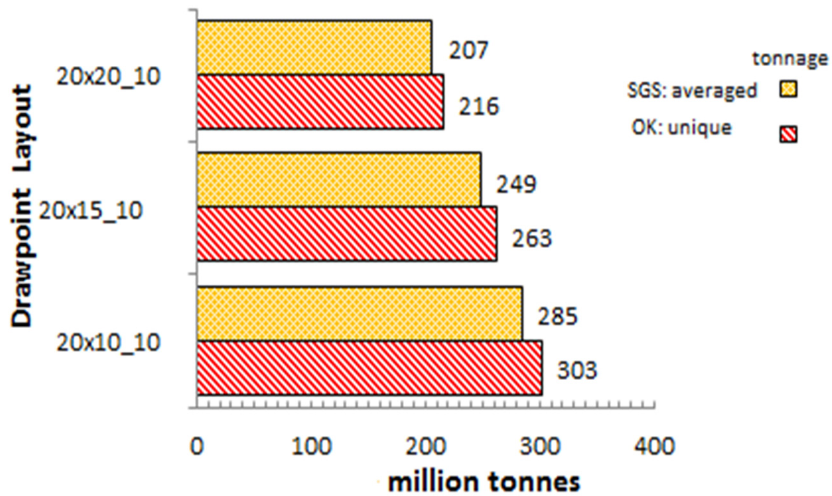


Fig 6. Tonnage (Mt) calculated within the three layouts of extraction

Table 4. Number of drawpoints and development cost for the three layouts

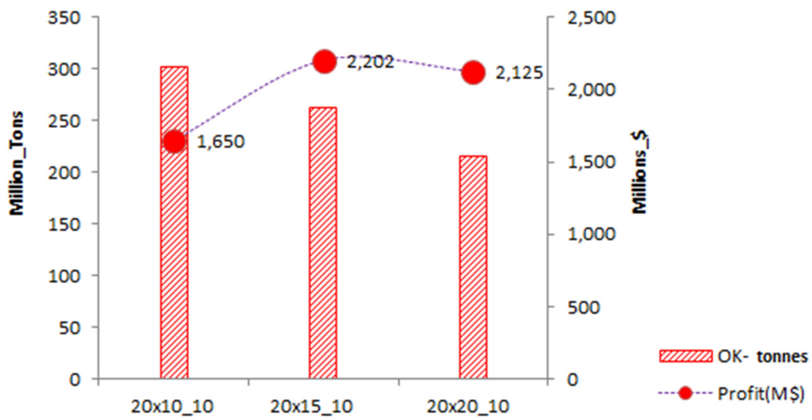
Block Cave Layout	# of Drawpoints	Development Cost ($/drawpoint)	Total development Cost ($M)
20×20_10	2296	150,000	344
20×15_10	3044	150,000	457
20×10_10	4570	150,000	686

Three response distributions (net values) of the simulated models are shown in Fig 8, in where the orange diamonds are the averages of the net values for each layout. These distributions are compared to three kriging responses that are displayed as three red circles. After a quick visual review, the distribution that appears to be the optimal is located within layout "20×15" for both OK and SGS.

Then the comparison of recoverable reserves between simulation and kriging for our block caving project is performed by using the layout with the optimized drawpoints. In other words, this calculation is conducted in the layout "20×15". A graphical representation of the comparison is illustrated in Fig 9. The Fig 9 generalized the process where the input models pass through a transfer function, which later will estimate the recoverable reserves from the block models generated by Kriging and simulation.

5. Results and Discussion

According to Table 3, the recoverable reserve that is estimated from the kriged model, with the optimal layout, is around 263 Mt with a grade of 0.65 % Cu. In contrast, the recoverable reserves that is estimated from the simulated models shows an average of 249 Mt, with an average grade of 0.65 % Cu.



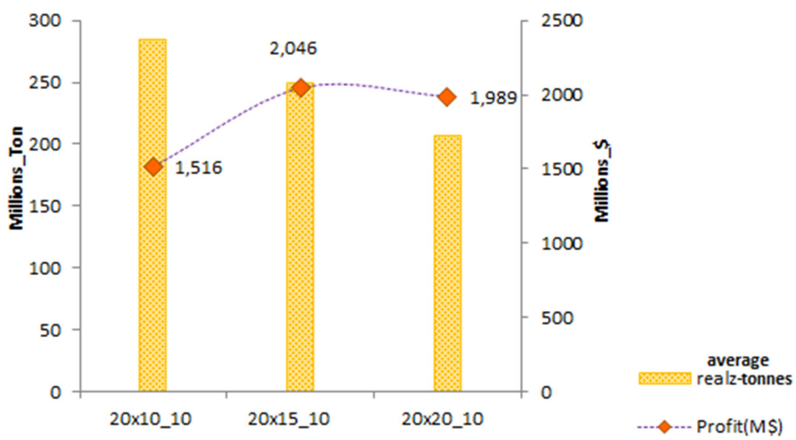


Fig 7. Optimized kriged tonnage and averaged simulated tonnage

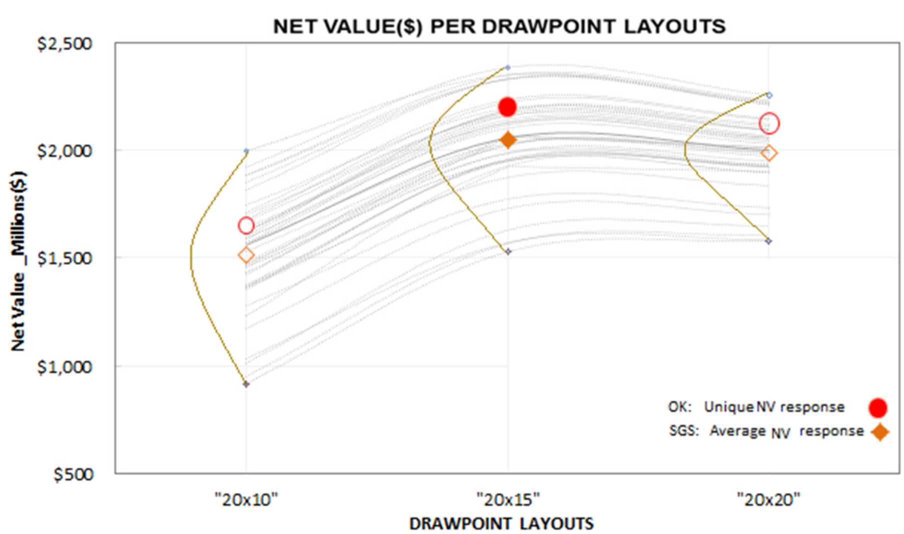


Fig 8. Three distributions of the Net-Value results ($M) based on kriged and simulation models

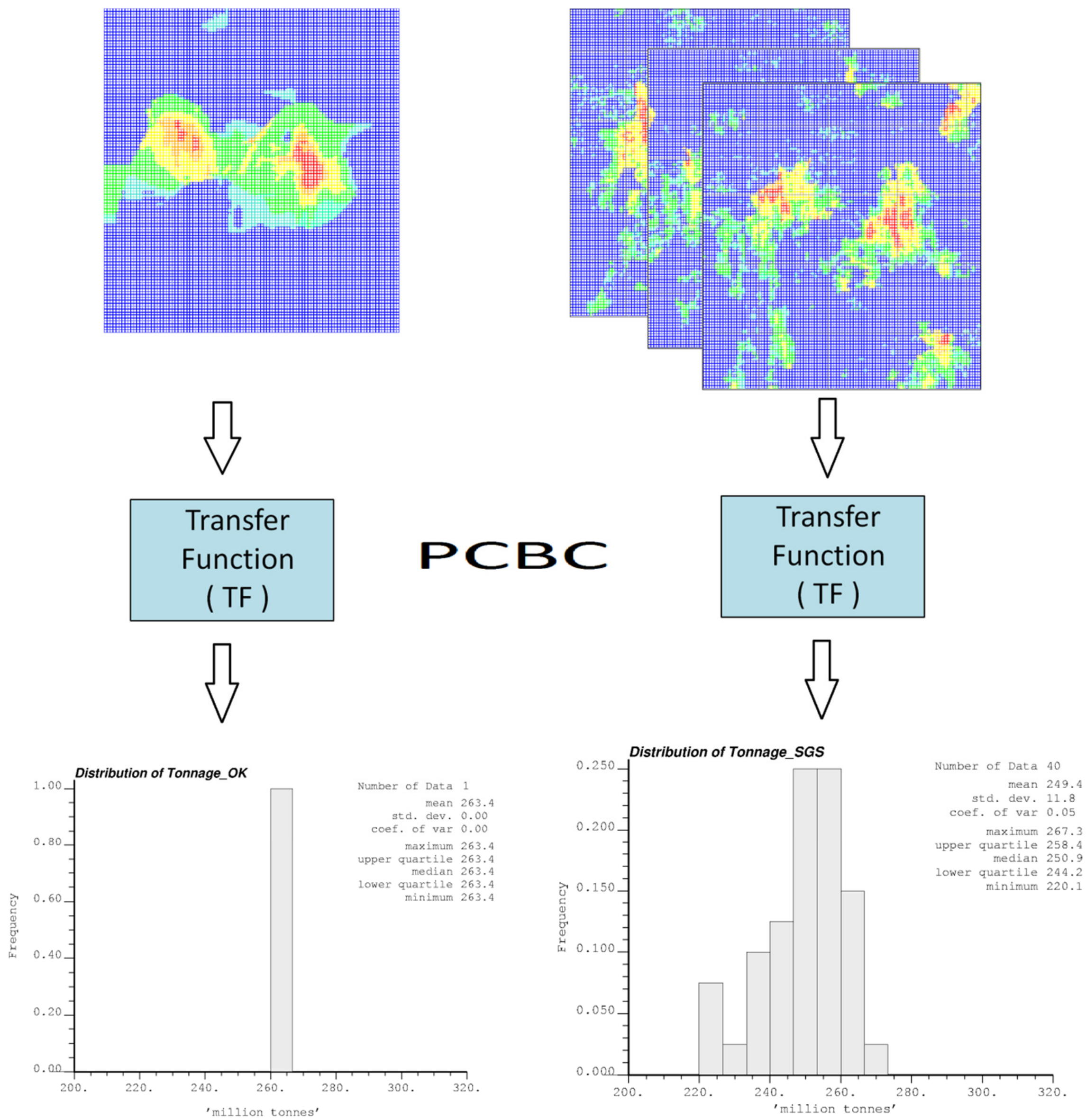


Fig 9. Comparison of recoverable reserves between simulation and kriging within the optimal layout

As it can be seen from the results and the histograms of the Fig 9, the smoothing effect of kriging is probably causing that the tonnages and net value to be greater than the averages of tonnage and net value from all 40 realizations. The usage of the response averages is highly recommended to get a trusted estimation of recoverable reserves (Clayton Deutsch, C. V., 2015). In other words, the average of the tonnages of copper that is generated by PCBC over the 40 realizations is much more reliable than a unique value given by PCBC over the kriging model. It worth to mention that, further uncertainty studies could be performed using these 40 response values. The assessments will certainly allow to evaluate risk and obtain a solid platform for decision making in this block caving project.

6. Conclusion

Even though kriging is widely use to estimate the recoverable resources in almost all types of mineral deposits, this paper illustrates some interesting ideas for using all realizations all the time in the block caving field. Then, using these equally probable models for the design of a block caving mine, and also in the estimation of minable reserves is here recommended. The reliable estimation of the mineral reserves is linked to the optimal layout of drawpoints at the extraction level. Then, it is important to remember that the optimal layout is highly relevant for any block caving mine, since this design has important effects in the evaluation of the economics of the project.

Despite the fact that the block caving design depends on many parameters and constraints and its evaluation is very challenging, an efficient extraction layout could be obtained by using a set of realizations. Managing a huge number of realizations is still a bit time consuming, hence the usage of 40 to 100 realizations is recommended. Moreover, hardware and software have been improving over the years. Therefore, the computer problems are not an issue anymore.

Overall, the comparison results of tonnage and grade as well as their profit based on kriging and realizations suggest that there is a potential opportunity to use SGS in the evaluation of block caving mines in order to obtain trusted estimations. However, additional uncertainty studies need to be developed in order to obtain a very solid floor for decision making.

7. References

[1]. Ahmed, H., Scoble, M., & Dunbar S. (2014). A comparison between Offset Herringbone and El Teniente underground cave mining extraction layouts using a discrete event simulation technique. *International Journal Journal of Mining Reclamation and Environment 30*(2):1-21.

[2]. Bhandari, D. (2007). Comparison of Recoverable Reserves Estimation Techniques, theses, University of Alberta ,Edmonton ,Canada.

[3]. Castro, R., Vargas, R., & Huerta F. (2012). Determination of drawpoint spacing in panel caving: a case study at El Teniente Mine. *The Journal of the southern African Institute of Mining and Metallurgy, vol. 112*.

[4]. Deutsch, C. V., & Journel, A. G. (1998). GSLIB: Geostatistical Software Library and User's Guide (2nd ed.). New York, NY: Oxford University Press.

[5]. Deutsch, C. V. (2015). All Realizations All the Time. CCG Paper 2015-101, *Centre for Computational Geostatistics*, University of Alberta, Edmonton, Canada

[6]. Diering, T., (2013). Reserve estimation using GEOVIA PCBC. Dessault Systemes Geovia Inc. Vancouver, British Columbia, Canada.

[7]. Laubscher, D (1994). Cave mining-the state of the art. *Journal of the South African Institute of Mining and Metallurgy*, pp. 279-293.

[8]. Laubscher, D.H. (2000). Block Caving Manual. International Caving Study, *JKMRC and Itasca Consulting Group, Inc.*

[9]. Leuangthong O., Schnetzler E. & Deutsch C.V. (2004), Geostatistical Modeling of McMurray Oil Sands Deposit. *CCG Paper 2004-309,* CCG, University of Alberta, Edmonton, Canada

[10]. Wilde B., & Deutsch C.V., (2005). A Short Note on the Comparison Kriging and the Average of Simulated Realizations. VCG Paper 2005-309, CCG, University of Alberta, Edmonton, Canada.

Quadratic Programming Application in Block-cave Mining

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Abstract

Block-cave mining with high rate of production and low operation costs seems to be one of the best options among underground mining methods and also a good alternative for deep open pit mines. Production scheduling is one of the critical steps in the block-caving design process. Optimal production schedule can add significant value to the block-cave mining project. Extraction of one drawpoint can change the production profile of its adjacent drawpoints. Therefore, block-cave mining operations can be complicated and behave as a non-linear phenomenon. So, production scheduling for this kind of operations with lots of involving dynamic parameters could be a big size problem in non-linear environment. A linear programming formulation may result in high levels of horizontal mixing between drawpoints. This paper uses mixed integer quadratic programming to model production scheduling in block-cave mining in order to reduce unexpected horizontal mixing, and as a result dilution during the life of the mine.

1. Introduction

Among underground mining methods, the operation cost of block caving is comparable to open pit mining which makes it attractive as an alternative for deep ore bodies. But the operation for block caving can be complicated because many constraints are involved and the material movement which directly affects the production can behave as a non-linear phenomenon. Extracting from a drawpoint can change the grade or tonnage of other drawpoints in its neighborhood. Maintaining a uniform extraction from drawpoints can reduce the unexpected movements of material. This will improve the production schedule, reduce the probability of horizontal mixing and as a result the dilution. In this research, production schedule for a block cave mining operation is modeled using mathematical programming. The model is mixed integer quadratic programming in which the objective function is quadratic and the constraints are linear. The proposed model is then tested for a real case block cave mine operation.

2. Summary of literature review

Operations research as a strong tool has been vastly used for optimizing production scheduling in mining projects. Some models have been proposed for block caving. Models are defined based on Linear Programming (Guest, Van Hout, & Von Johannides, 2000; Hannweg & Van Hout, 2001; Winkler, 1996), Mixed-Integer Linear Programming (Alonso-Ayuso, et al., 2014; Chanda, 1990; Epstein, et al., 2012; Guest, et al., 2000; Parkinson, 2012; Pourrahimian, 2013; Rahal, 2008; Rahal, Dudley, & Hout, 2008; Rahal, Smith, Van Hout, & Von Johannides, 2003; Rubio, 2002; Rubio & Diering, 2004; Smoljanovic, Rubio, & Morales, 2011; Song,

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1989; Weintraub, Pereira, & Schultz, 2008; Winkler, 1996), and Quadratic Programming (Diering, 2012; Rubio & Diering, 2004). In the case of block-cave scheduling, a linear programming (LP) formulation will always seek to take the maximum tons from the highest value drawpoints and the least tons from the lower-valued drawpoints (Diering, 2012). As a result, this kind of scheduling may result in high levels of horizontal mixing between drawpoints because draw columns have different heights. Table 1 summarizes the advantages and disadvantages of methodologies examined in previous studies (Khodayari & Pourrahimian, 2015b).

Table 1. Advantages and disadvantages of applied mathematical methodologies in block caving

Methodology	**Features**	
LP	*Advantage*	• LP method has been used most extensively • It can provide a mathematically provable optimum schedule
	Disadvantage	• Straight LP lacks the flexibility to directly model complex underground operations which require integer decision variables • Mine scheduling is too complex to model using LP and the only possible approach is to use some combination of theoretical and heuristic methods to ensure a good, if not optimal schedule
MILP	*Advantage*	• Computational ease in solving a MIP problem (and MILP) is dependent upon the formulation structure • MILP could be used to provide a series of schedules which are marginally inferior to a provable optimum • MILP is superior to simulation when used to generate sub-optimal schedules, because the gap between the MILP feasible solution and the relaxed LP solution provides a measure of solution quality • MILP can provide a mathematically provable optimum schedule
	Disadvantage	• It is often difficult to optimize large production systems using the branch-and-bound search method • The block-caving process is non-linear (the tons which you mine in later periods will depend on the tons mined in earlier periods), so it would not be appropriate to use LP for production scheduling in block caving
QP	*Advantage*	• Since the block-caving process is non-linear, QP could be an appropriate option to model it • It can find solutions in the interior of the solution space, which results in an even height of extraction as well as lower horizontal mixing between drawpoints
	Disadvantage	• Solving this kind of problem could be a challenge.

Khodayari and Pourrahimian (2015b) presented a comprehensive review of operations research in block-caving production scheduling, and summarized authors' attempts to develop methodologies to optimize production scheduling in block caving.

3. Mathematical formulation

In this paper, the production scheduling problem for a block-cave mining operations is modelled using mixed-integer quadratic programming (MIQP). IBM/CPLEX is used to model and solve the optimization problem. The model's related indices, variables, and parameters are discussed in this section.

Notation

- *Indices*

$t \in \{1,...,T\}$	Index for scheduling periods
$n \in \{1,...,N\}$	Index for drawpoints
m	Index for a drawpoint belonging to the set S^n

- *Sets*

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

- *Variables*

$DP_n^t \in [0,1]$	Depletion Percentage which is the portion of draw column *n* which has been extracted till period *t* (continuous variable)
$X_n^t \in [0,1]$	Continuous decision variable that represents the portion of draw column *n* which is extracted in period *t*
$Y1_n^t \in \{0,1\}$	Binary variable which determines whether drawpoint *n* in period *t* is active ($Y1_n^t = 1$) or not ($Y1_n^t = 0$)
$Y2_n^t \in \{0,1\}$	Binary variable which determines whether drawpoint *n* till period *t* (periods 1, 2,..,t) has started its extraction ($Y2_n^t = 1$) or not ($Y2_n^t = 0$)

- *Parameters*

$ext\,\mathrm{ton}_n^t$	Optimum tonnage of extraction for the drawpoint *n* at period *t* based on the solution of the production scheduling problem (based on problem optimization, it is an output of model)
$\exp ton_n^t$	Objective tonnage of extraction for the drawpoint *n* at period *t* based on the production goals (input)
g_n	Average copper grade of draw column associated with drawpoint *n*
ton_n	Ore tonnage of draw column associated with drawpoint *n*
$M_{\min}$	Minimum mining capacity based on the capacity of mining equipment
$M_{\max}$	Maximum mining capacity based on the capacity of mining equipment
$G_{\min}$	Minimum production grade

$G_{\max}$	Maximum production grade
$ActMin$	Minimum number of active drawpoints in each period
$ActMax$	Maximum number of active drawpoints in each period
M	An arbitrary big number

3.1 Objective function

Production goals determine the required tonnage of extraction in a mining project. There are always some constraints that control the goals. In this research, the optimization problem is looking for the best solution to reduce the gap between the expected production and the optimal production considering the related constraints. The objective function, Eq. (1), is going to minimize the deviation of the drawpoint extraction and the expected extraction for each drawpoint in each period of production:

$$Minimize \ \sum_{t=1}^{T}\sum_{n=1}^{N}(ext\,\mathrm{ton}_n^t - \exp ton_n^t)^2 = \sum_{t=1}^{T}\sum_{n=1}^{N}\left[(ton_n \times X_n^t) - \exp ton_n^t\right]^2 \tag{1}$$

Extraction from drawpoints while having a uniform extraction surface is one of the most important concerns in block-cave mining. It will reduce the dilution, which can be improved by solving this optimization problem.

3.2 Constraints

There are many geotechnical, operational, and economic constraints related to mining projects, which limit the whole system in achieving the operational and strategic plans. This research will try to make sure that related constraints are considered so that the model's results can be applicable in real case block-cave mining.

Binary variables

Two sets of binary variables are used to be able to define the related constraints in the model, Y1 and Y2. Each drawpoint has both variables (Y1 and Y2) per each period.

The first set of binary variable (Y1) determines whether drawpoint *n* is active in period *t* or not; if any extraction from drawpoint *n* at period *t* occurs, it means that the drawpoint is active ($X_n^t > 0$) then $Y1_n^t = 1$ and if there is no any extraction ($X_n^t = 0$) it means that the drawpoint is not active then $Y1_n^t = 0$. To formulate this concept, equations (2) and (3) are used.

$$\forall t \in T \ \& \ n \in N \rightarrow \quad Y1_n^t - Mx_n^t \le 0 \tag{2}$$

$$\forall t \in T \ \& \ n \in N \rightarrow \quad x_n^t - Y1_n^t \le 0 \tag{3}$$

The second set of binary variable (Y2) determines whether the depletion percentage of drawpoint *n* in period *t* is 0 or not. Depletion percentage (DP) is the summation of the *X* values for drawpoint *n* from period 1 to period *t* based on the draw rate curve.

$$\forall n \in N \rightarrow \quad DP_n^t = \sum_{t=1}^{t} x_n^t \tag{4}$$

If the depletion percentage is 0 ($DP_n^t = 0$) then $Y2_n^t = 0$; otherwise $Y2_n^t = 1$. Two equations are defined for this set:

$$\forall t \in T \ \& \ n \in N \rightarrow \quad DP_n^t - Y2_n^t \le 0 \tag{5}$$

$$\forall t \in T \ \& \ n \in N \rightarrow \quad Y2_n^t - (M \times DP_n^t) \leq 0 \tag{6}$$

Mining capacity

This constraint considers the total production (extraction from all drawpoints) for each period of time. It is determined based on the equipment and the scale of the mining operations. It helps to make sure that the system is working in an optimal capacity.

$$\forall t \in T \rightarrow \quad M_{\min} \leq \sum_{n=1}^{N} ton_n \times X_n^t \leq M_{\max} \tag{7}$$

Average grade of production

The average grade of the extracted material should be in an acceptable range. This constraint helps to have a uniform extraction of the ore during the mine life and can be determined based on processing plant requirements. Equations (8) and (9) control this constraint.

$$\forall t \in T \rightarrow \quad G_{\min} \times (\sum_{n=1}^{N} ton_n \times X_n^t) \leq \sum_{n=1}^{N} g_n \times ton_n \times X_n^t \tag{8}$$

$$\forall t \in T \rightarrow \quad \sum_{n=1}^{N} g_n \times ton_n \times X_n^t \leq G_{\max} \times (\sum_{n=1}^{N} ton_n \times X_n^t) \tag{9}$$

Reserve

The best height of draw (BHOD) is calculated before applying the mathematical model. This constraint ensures that the fractions of draw columns that are extracted over the scheduling periods are going to sum up to 1, which means all the material within the draw column, based on the BHOD, is going to be extracted.

$$\forall n \in N \rightarrow \quad \sum_{t=1}^{T} X_n^t = 1 \tag{10}$$

Number of allowable active drawpoints

This constraint controls minimum and maximum number of active drawpoints at each period of time.

$$\forall t \in T \rightarrow \quad ActMin \leq \sum_{n=1}^{N} Y1_n^t \leq ActMax \tag{11}$$

Development direction and mining precedence

Two of the key steps in block-caving operation scheduling are development direction and drawpoints' precedence determination. Extraction of each drawpoint can be started if the predecessor drawpoints have been started before. The precedence constraint is defined by Eq (12):

$$\forall n \in N \ \& \ t \in T \ \& \ m \in S^n \rightarrow \quad Y2_n^t \leq Y2_m^t \tag{12}$$

Eq. (12) ensures that all drawpoints belonging to relevant set, S^n , are started prior to the extraction of drawpoint *n*. This set is defined based on the method presented by Khodayari and Pourrahimian (2015a).

Continuous mining

Extraction from each drawpoint must be continuous. Eq. (13) ensures that if extraction from a drawpoint starts in a period, at least a portion of the draw column associated with the drawpoint is extracted based on draw rate constraint until all of the material within that drawpoint has been extracted. It should be noted that Eq. (13) works interactively with equations (2), (3), (4), (5), and (6).

$$\forall n \in N \,\&\, t \in T \rightarrow \qquad Y1_n^t + DP_n^{t-1} \geq Y1_n^{t-1} \tag{13}$$

4. Computational experience

A real case data for a copper block-cave mine operation is implemented to test the MIQP model. Mine development has been finished and the life of the mine is 10 years. The mine has been designed and the production is going to be based on 102 drawpoints. Figure 1 shows the plan view of drawpoints and the advancement direction determined by the methodology presented by Khodayari and Pourrahimian (2015a). Based on the reserve estimation, total tonnage is 13.45 million tonne with the average weighted grade of %1.33 of Cu. The scheduling parameters are presented in Table 2.

The optimization model contains 5100 variables in which the first 1020 variables are continuous and the rest are binary variables. The objective function is going to minimize the difference between an initial tonnage of extraction and the tonnage of extraction which is based on the production schedule.

The resulted tonnage and grade of production during the life of mine shows that the MIQP model tries to produce an even amount during the life of the mine while satisfying the mining capacity and grade constraints (Fig. 2).

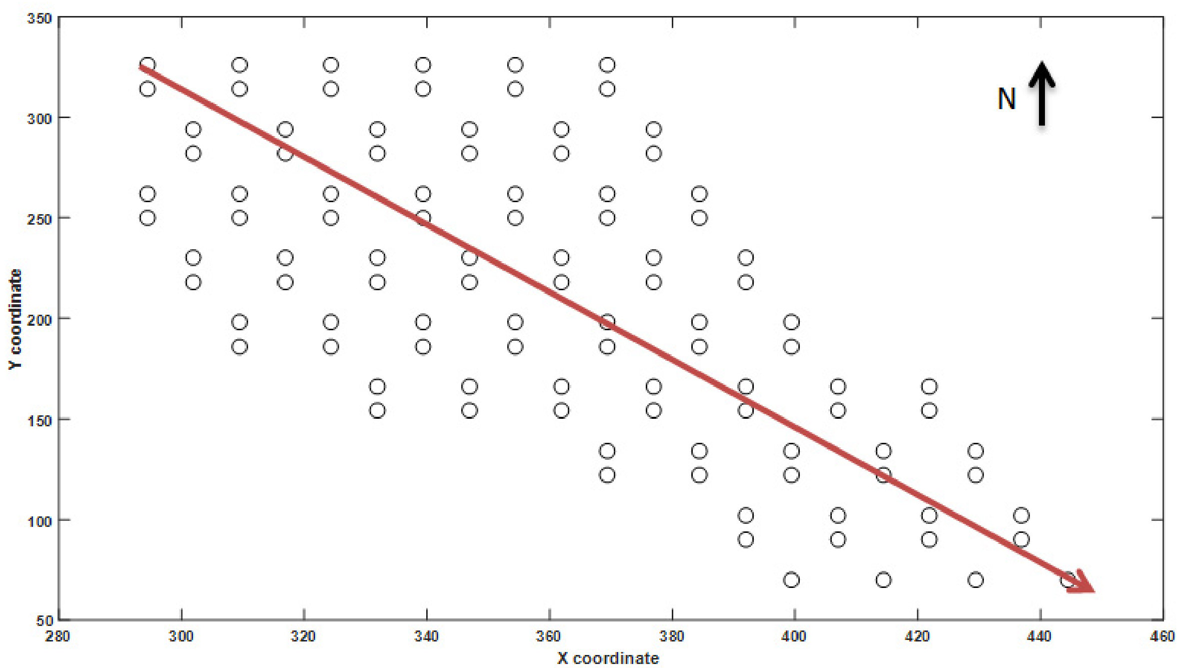

Fig. 1. Plan view of the drawpoints and determined advancement direction

Table 2. Scheduling parameters

Parameter	Description	Value	unit
T	Mine Life	10	Year
G_{min}	Minimum grade	1.1	%
G_{max}	Maximum grade	1.5	%
M_{min}	Minimum mining capacity	0.5	Mt
M_{max}	Maximum mining capacity	1.4	Mt
$ActMin$	Minimum number of active drawpoints	0	-
$ActMax$	Maximum number of active drawpoints	45	-
$EGap$	MIP gap	5	%

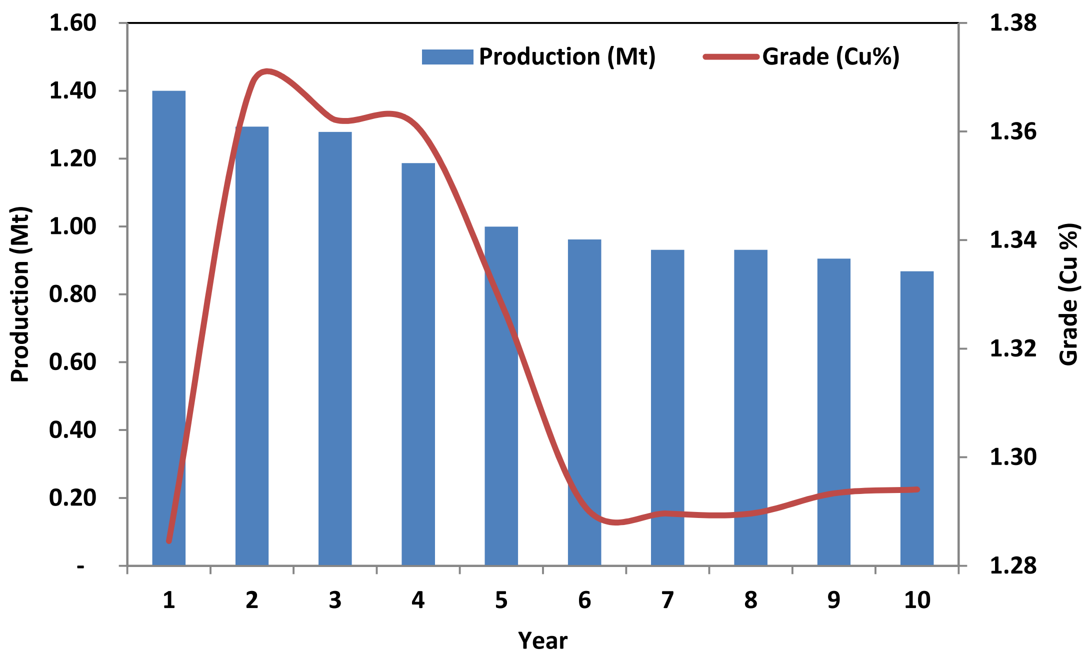

Fig. 2. Total production and average grade during the life of mine

Number of active drawpoints during the life of mine shows that the model is following the related constraints (Fig. 3). Figure 4 shows the trend and how the active drawpoints affect their adjacent drawpoints based on the defined advancement direction and precedence between drawpoints.

Figure 5 shows that the profile of extraction resulted from MIQP model is uniform. It is shown that the extraction starts from West at year one and then expands to the centre of the mine at the second year. The extraction continues to the eastern area in years 4 and 5. There is not that much changes for the last two years because extraction from almost all drawpoints has already been started. It can be seen that the MIQP model can generate a practical profile with low probability of horizontal mixing.

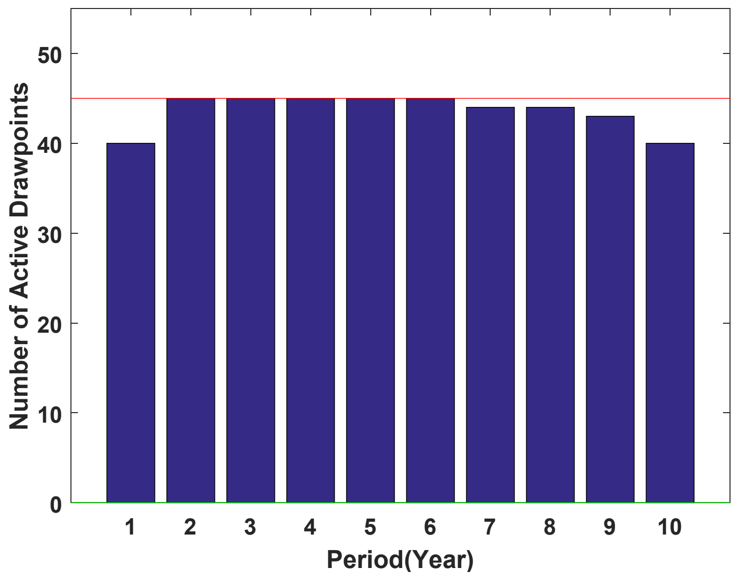

Fig. 3. Number of active drawpoints during the life of mine (the red and green lines are the defined upper and lower bounds, respectively)

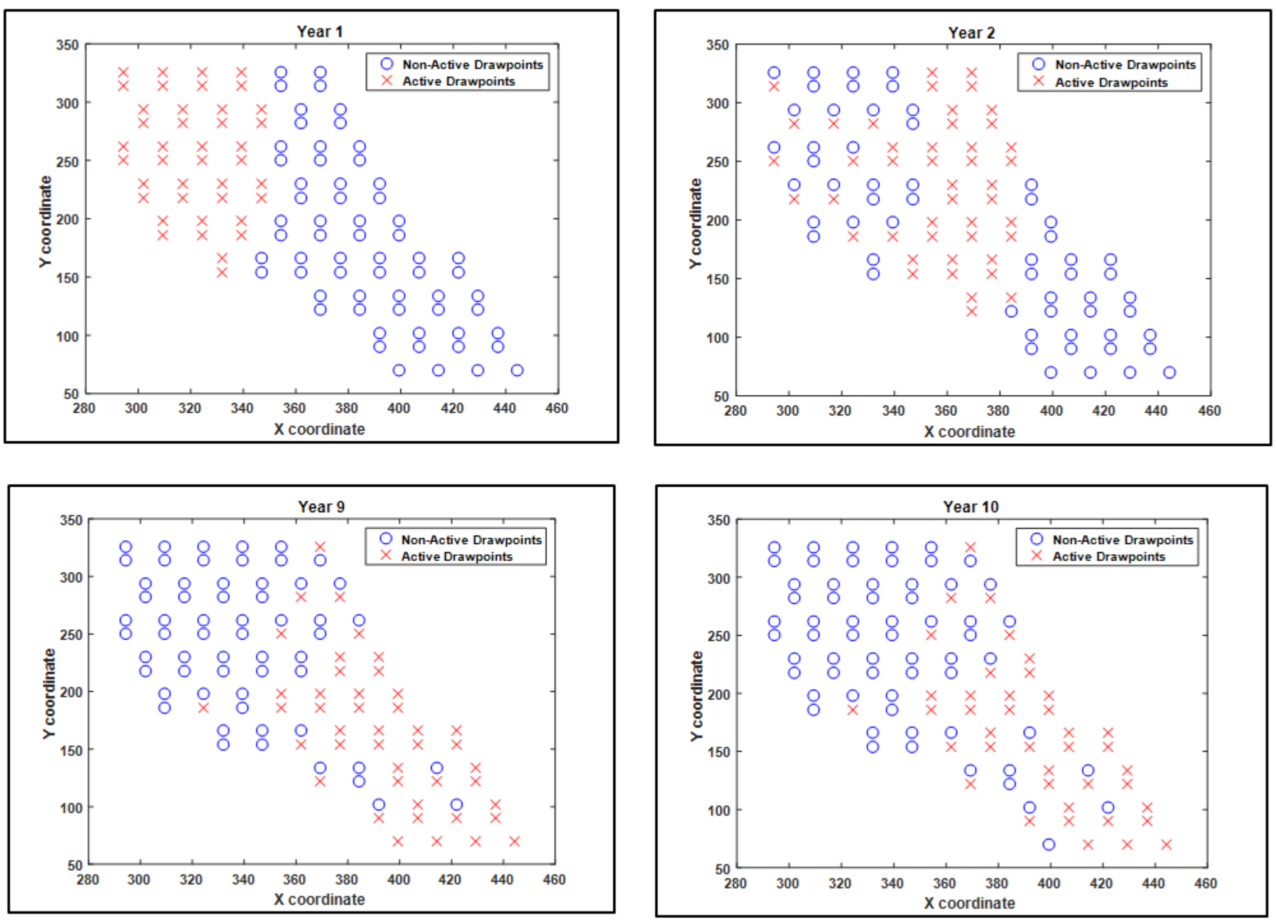

Fig. 4. Number of active drawpoints during the life of mine (years 1,2, 9, and 10)

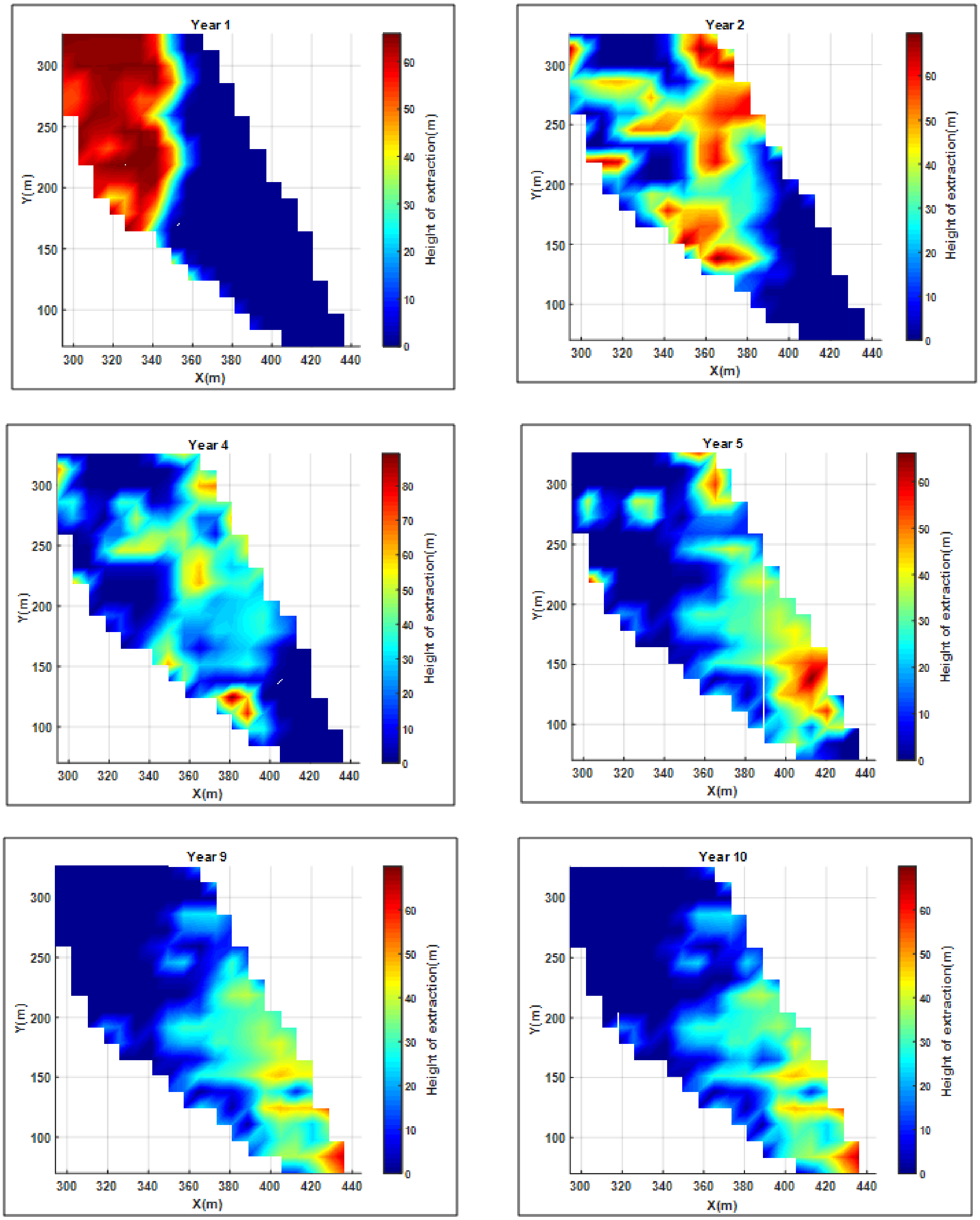

Fig. 5. Generated height of extraction during the life of the mine for different years

5. Discussion

In this research, mixed-integer quadratic programming (MIQP) as a non-linear methodology was used to model production scheduling in block-cave mining operation. The objective function was minimization of the difference between the extraction from drawpoints and an initial tonnage to generate a uniform extraction profile. The uniform extraction profile can reduce the horizontal movements and as a result the dilution. Although the solution time for the MIQP model is longer than the MILP models, the MIQP model extracts from the drawpoints smoothly with a very low fluctuation of tonnage and grade during the life of the mine. This will generate uniform extraction profile with lower dilution.

6. References

[1] Alonso-Ayuso, A., Carvallo, F., Escudero, L. F., Guignard, M., Pi, J., Puranmalka, R., et al. (2014). Medium range optimization of copper extraction planning under uncertainty in future copper prices. *European Journal of Operational Research, 233(3),* 711-726.

[2] Chanda, E. C. K. (1990). An application of integer programming and simulation to production planning for a stratiform ore body. *Mining Science and Technology, 11(2)*, 165-172.

[3] Diering, T. (2012). Quadratic Programming applications to block cave scheduling and cave management. *Paper presented at the Massmin 2012.*

[4] Epstein, R., Goic, M., Weintraub, A., Catalán, J., Santibáñez, P., Urrutia, R., et al. (2012). Optimizing Long-Term Production Plans in Underground and Open-Pit Copper Mines. *Operations Research, 60(1)*, 4-17.

[5] Guest, A. R., Van Hout, G. J., & Von Johannides, A. (2000). An Application of Linear Programming for Block Cave Draw Control. *Paper presented at the MassMin, Brisbane, Australia*.

[6] Hannweg, L. A., & Van Hout, G. J. (2001). Draw control at Koffiefontein Mine. *Paper presented at the 6th International Symposium on Mine Mechanization and Automation.*

[7] Khodayari, F., & Pourrahimian, Y. (2015a). Determination of development precedence for drawpoints in block-cave mining. *Paper presented at the 5th International Symposium Mineral Resources and Mine Development (AIMS 2015).*

[8] Khodayari, F., & Pourrahimian, Y. (2015b). Mathematical programming applications in block-caving scheduling: a review of models and algorithms. *Int. J. of Mining and Mineral Engineering 2015 - Vol. 6, No.3 pp. 234 - 257, 6(3)*, 234-257.

[9] Parkinson, A. (2012). Essays on Sequence Optimization in Block Cave Mining and Inventory Policies with Two Delivery Sizes. The University Of British Columbia, The University Of British Columbia.

[10] Pourrahimian, Y. (2013). Mathematical programming for sequence optimization in block cave mining. Unpublished Ph.D., University of Alberta (Canada).

[11] Rahal, D. (2008). Draw Control in Block Caving Using Mixed Integer Linear Programming. The University of Queensland.

[12] Rahal, D., Dudley, J., & Hout, G. v. (2008). Developing an optimised production forecast at Northparkes E48 mine using MILP. *Paper presented at the 5th International Conference and Exhibition on Mass Mining*, Luleå Sweden.

[13] Rahal, D., Smith, M., Van Hout, G., & Von Johannides, A. (2003). The use of mixed integer linear programming for long-term scheduling in block caving mines. *Application of Computers and Operations Research ill the Minerals Industries, South African Institute of Mining and Metallurgy*, 123-132.

[14] Rubio, E. (2002). Long term planning of block caving operations using mathematical programming tools. The University of British Columbia.

[15] Rubio, E., & Diering, T. (2004). Block cave production planning using operation research tool. *Paper presented at the Massmin 2004*, Santiago, Chile.

[16] Smoljanovic, M., Rubio, E., & Morales, N. (2011). Panel Caving Scheduling Under Precedence Constraints Considering Mining System. *Paper presented at the 35th APCOM Symposium*, Wollongong, NSW, Australia.

[17] Song, X. (1989). Caving process simulation and optimal mining sequence at Tong Kuang Yu mine, China.

[18] Weintraub, A., Pereira, M., & Schultz, X. (2008). A Priori and A Posteriori Aggregation Procedures to Reduce Model Size in MIP Mine Planning Models. *Electronic Notes in Discrete Mathematics 30*, 297–302.

[19] Winkler, B. M., (1996). Using MILP to Optimize Period Fix Costs in Complex Mine Sequencing and Scheduling Problems. *Paper presented at the Twenty sixth proceedings of the application of computers and operations research in the minerals industry (APCOM)*.

Determination of Optimum Drawpoint Layout in Block caving

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Abstract

In a context of modern geostatistics, sequential Gaussian simulation has become a very popular technique to evaluate mining projects nowadays (Clayton V. Deutsch, 2015). Although realizations are used in different mining applications to solve specific mining issues for planning and production, there is still potential in the mining industry for using simulation. For instance, the usage of all realizations to generate optimal drawpoint spacing for a block cave is one of these potential applications.

There is a good amount of research related to block caving design, which includes studies about drawpoint spacing within the extraction level. Nonetheless, none of these studies considers the geostatistical simulation as instrument to obtain the drawpoint spacing for the block caving layouts. 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 looking for forms to maximize the profit of their projects in surface and underground environments. For instance, among the underground operations, block caving has shown to be one of the most preferred mining methods in the last decade. The reasons are many, but one of them is because this type of massive mining is commonly used for the exploitation of deep and large low-grade material (Castro et al., 2012). Despite the fact that block caving is a very challenging mining method due to its complexity, this method is the most profitable among the underground types, so that block caves can be only compared with the open-pit mines, economically speaking. However, as mentioned above, block-cave mines depend on many constraints and parameters. Between these parameters, the drawpoint spacing is certainly the most critical one for designing the extraction layout in a block-caving project since this spacing causes important impacts in the final profitability of the mine. Several studies have been made about drawpoint spacing. However, none of them had used geostatistical simulation to solve this problem. Here is presented a proposed technique based on Sequential

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Gaussian Simulation, and using "All Realizations All the Time" to obtain the optimal drawpoint spacing.

To better understand this approach, a small study is developed; it provides a concise illustration to guide the reader for performing a design of an optimal drawpoint spacing that is a relevant feature in the extraction layout.

The study begins with an exploratory and analysis of the drillhole composites. After that, the variography is conducted. It is important to mention that, all the exploration, compositing, variography, and SGS modelling is performed by using the geostatistical tools of GSLIB catalog (Deutsch, C. V., & Journel, A. G. 1998). After having the explored data, a modelling process of the main variable (Cu) is developed. The modelling is performed by SGS. The simulation outputs consist of a group of 40 realizations that are imported to Gems (Geovia, Dassault Systemes) as 40 block models where the main variable is copper. Then, a following setting is performed in a block cave module, called PCBC. Several assumptions are considered as well as mining parameters has been set in PCBC-Gems. Parameters such as, development cost, mining cost, rock density, and others are considered as input data within PCBC-Gems. The PCBC module is used as the transfer function and generates a tremendous amount of important data that could be used for further analysis. From the generated data, the net value is the most important one to our purpose because the objective of this study is the search of the optimal drawpoint spacing to maximize the profit of a block-caving project.

The study results demonstrate that SGS is a very useful tool to obtain the optimal drawpoint spacing. Then, as mentioned above, the design of the best possible drawpoint spacing is a relevant task to maximize the profitability of any block cave mine.

2. Review of the Fundamental Principle of Simulation Applied to this Study

In modern geostatistics, the Monte Carlo Simulation (MCS) is a very well know computational algorithm; it relies on random samples to obtain some results. This algorithm is represented, in general, by the formulation of a problem with input variables, a transfer function, and the computed response variables which are assembled into a probability distribution (Clayton V. Deutsch, 2015), (Fig 1). Moreover, it is worth to mention that, the obtained distribution is also used to understand the uncertainty.

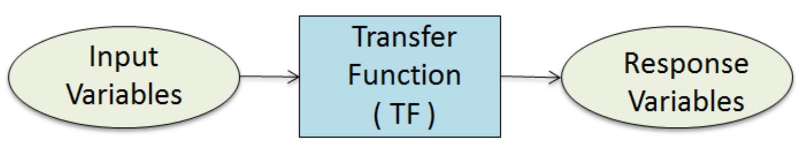


Fig 1. Monte Carlo Simulation concepts (Clayton V. Deutsch, 2015)

This paper illustrates a number of steps where the MCS is mimicked to explain how useful this method can be to solve mining-related problems.

First of all, the input variable (Cu) is simulated in a 20×20×15 grid, 40 realizations are obtained from SGS. For our case, the transfer function is an inner algorithm to calculate the net value ($) that is inside PCBC-Gems. It is important to mention that PCBC need several engineering and economical parameters such as mining and developing cost; and some assumption such as fragmental size, proposed drawpoint spacing type, etc. The transfer function converts the simulated copper values of every realization into response variables. In other words, one realization which is considered as one block model is converted into one net value ($), and then the 40 net values are organized in a distribution of response variables to obtain the mean (average) and the variance, for further uncertainty assessment. Then, to obtain the optimal extraction layout, several distributions need to be evaluated. Strictly speaking, each distribution belongs to a different layout.

3. Metodology and Experimental Work Flow

Further explanation of the concepts and results will be illustrated through a case study. The drillhole data was resampled from a confidential block model provided by Geovia, Dassault Systemes. In other words, a type of synthetic data is used throughout the study.

To show the proposed method, the present experiment is divided by three main stages, and they are explained as follows. First, a brief data analysis and a geostatistical simulation study are performed. Second, the setting of mining parameters and calculation are made in PCBC-Gems; PCBC is considered as the transfer function. Third, the results generated in PCBC-Gems for each of the layouts are processed in terms of net value to finally obtain the optimized block-caving layout at the initial extraction elevation.

Furthermore, the optimized block-caving layout is tested in four different extraction elevations in order to search for the best level of extraction based on the best net values.

4. Data Analysis and Variography

The first step includes the exploratory and the spatial analysis of the continuous data. As mention previously, the data was extracted from a former block model, and the copper (Cu) is the principal variable for a total of 55 drillholes. A 3-D plot of the drillholes is shown on the left side of Fig 2. While, on the right side, the 2-D location map of the composites is illustrated, this map has been generated with a program of GSLIB catalog (Deutsch, C. V., & Journel, A. G. 1998).

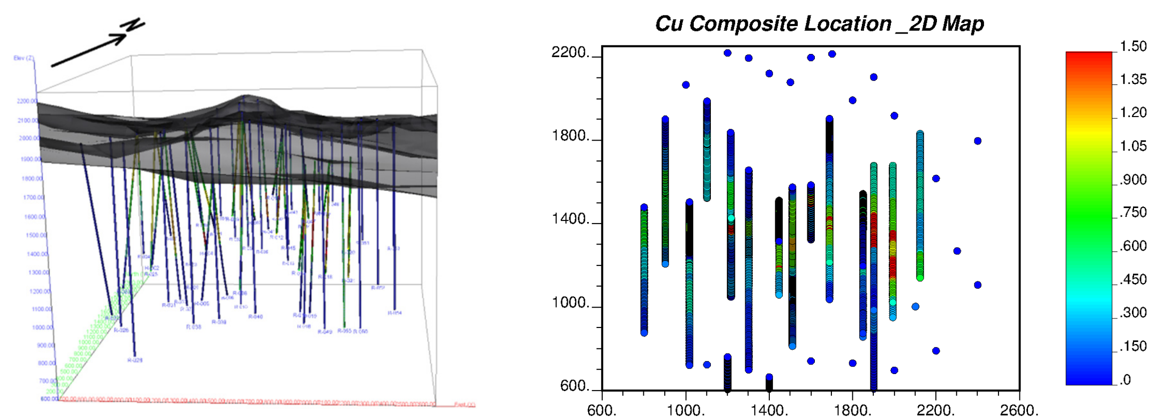


Fig 2. On the left, 3-D locations of drill holes, while a 2-D map of composites shown on the right

The drilling assays are composited to 10m. Each composite contains the x, y, z, copper(Cu), and lithology. After an exhaustive exploratory data analysis of all composites is performed, the global mean of the copper grade obtained is 0.229 % with a variance of 0.122. Fig 3 shows the global histograms.

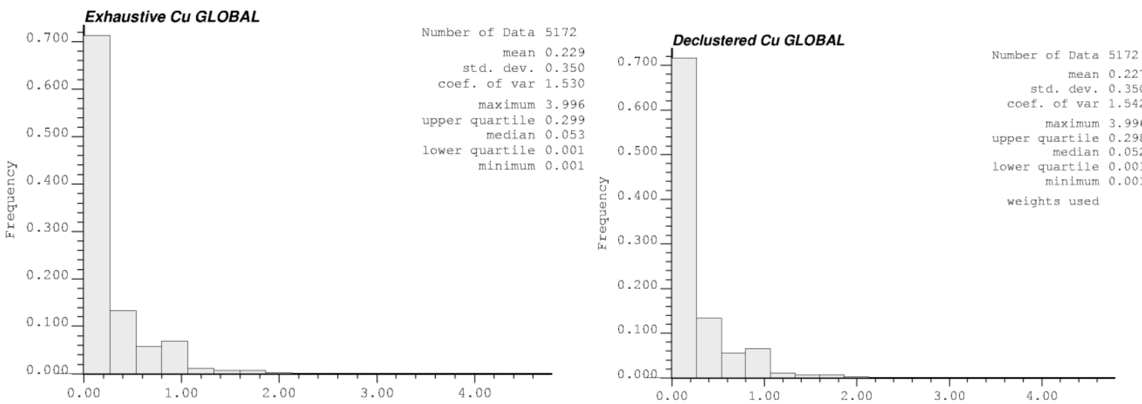


Fig 3. These two plots show the copper global histograms. The left plot is generated with no weights

The decision of stationarity is important before further statistical and geostatistical analysis is performed. Therefore, an implicit rock modeling is made with software based on Random Distance Function, shown in Fig 4. Then, the domain selection was decided based on the geological values of the data to simplify the process. The project is separated in two domains: Domain 1 and Domain 2. According to the geology of the area, Domain 1 is related to a porphyry intrusion, while the Domain 2 represents the country rock of the area, as shown in Table 1 and Fig 4.

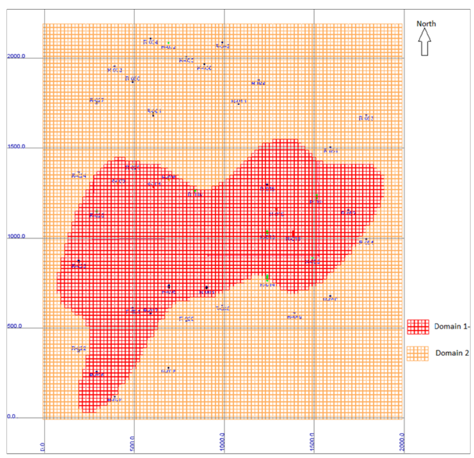


Fig 4. Two domains are Illustrated in a surface plot: Domain 1, and Domain 2

Table 1. Domain: two rock types and their codes

Rock Type	Domain Code
Intrusive	1
Country rock	2

Notice that, decision of stationarity is made for grouping the copper values within two distributions (domains). The domains are used to conduct further exploration and variography of composited data, so that the simulation modelling can be performed.

After the decision of stationarity is defined, cell declustering needs to be performed, ideally for the two domains. The DECLUS program (Deutsch and Journel, 1998) is used to get the declustering weights. The main idea is that values in cells with more data receive less weight than those in sparsely sampled places. To simplify the modeling process on the present study, only one cell size is chosen, for both domains. Fig 5 presents a plot that illustrates the possible cell sizes versus the declustered means. Then, according to the study data, the cell size 500×500 is elected.

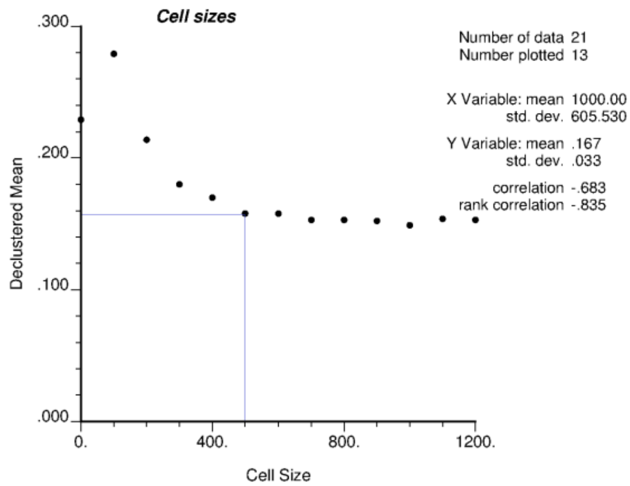


Fig 5. Cell size selection (500m x 500m) to generate the decluttering weights

Given the declustering weights, further histogram analysis over each domain is conducted. These plots are obtained with both declustering weights, and without them. As expected, histograms created with declustered weights show a small decrease in the mean and variance of copper values. Histograms of the two data-set distributions are shown in Fig 6. Plots present distributions with high-tail, looking like lognormal distributions. In both cases the tails contain few values. Those features are common in massive intrusive deposits, such as copper porphyry ones, and where the country rock (Domain 2) contains some mineralization. Cumulative plots are shown in Fig 7, thus the domain 2 clearly show that almost 80 percent of its copper values are close to zero. The weighted mean of the copper grade obtained for Domain 1 is of 0.42% cu with a weighted variance of 0.16, while the weighted mean of the copper grade obtained within Domain 2 is 0.04% with a weighted variance of 0.01.

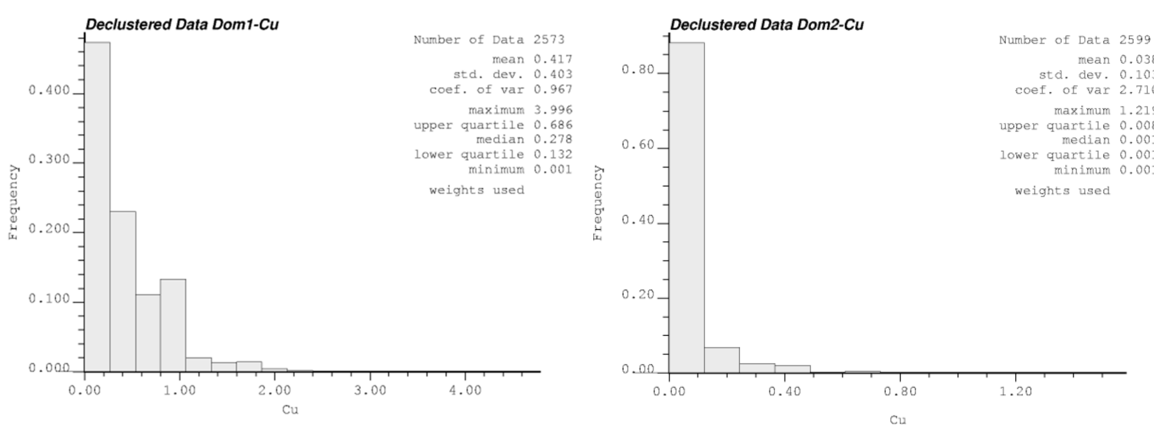


Fig 6. Histograms of the two domains, using the weights

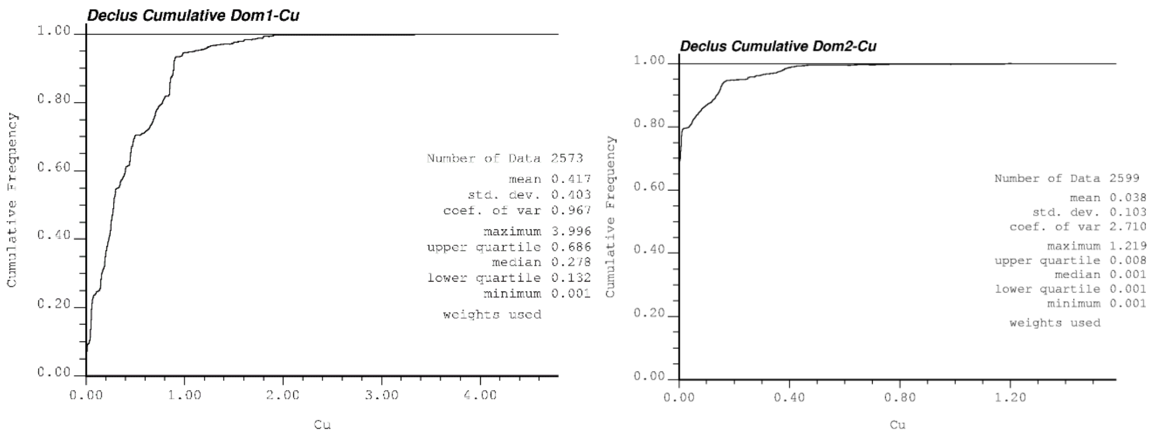


Fig 7. Cumulative plots for the two domains

Geostatistical simulation will require not only the declusted set of data, but also this data will need to be transformed into normal score units. Hence, our data is transformed to normal score values using the NSCORE program (Deutsch and Journel, 1998). The two declustered and normal scored distribution are shown in Fig 8.

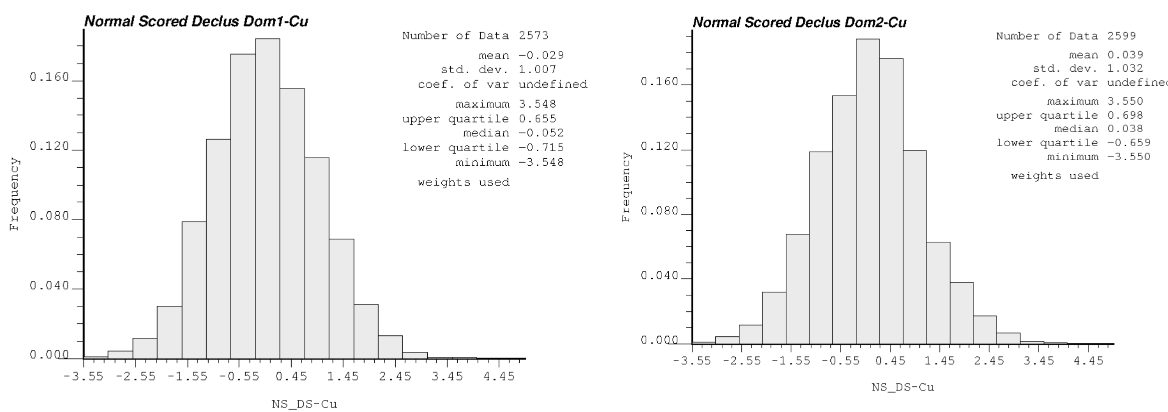


Fig 8. Two normal scored histograms for the two domains.

Modeling the spatial continuity of the rock indicator and copper grade using variograms is an essential step before the SGS is performed. Variograms are the common spatial measure of continuity which shows the variability of grades with distance. This study includes two types of variogram modelling. One of them is the indicator variogram modeling, and the second one is the continuous variogram modeling. The experimental and fitted variogram models in major, minor and vertical directions are displayed in Fig 9.

For the continuous variable, all the directional experimental variograms have been calculated using the GAMV program (Deutsch and Journel, 1998). The VMODEL program was used to fit the anisotropic variograms. These models contain two nested spherical structures, and the major and minor directions are 90 and 0 degrees respectively.

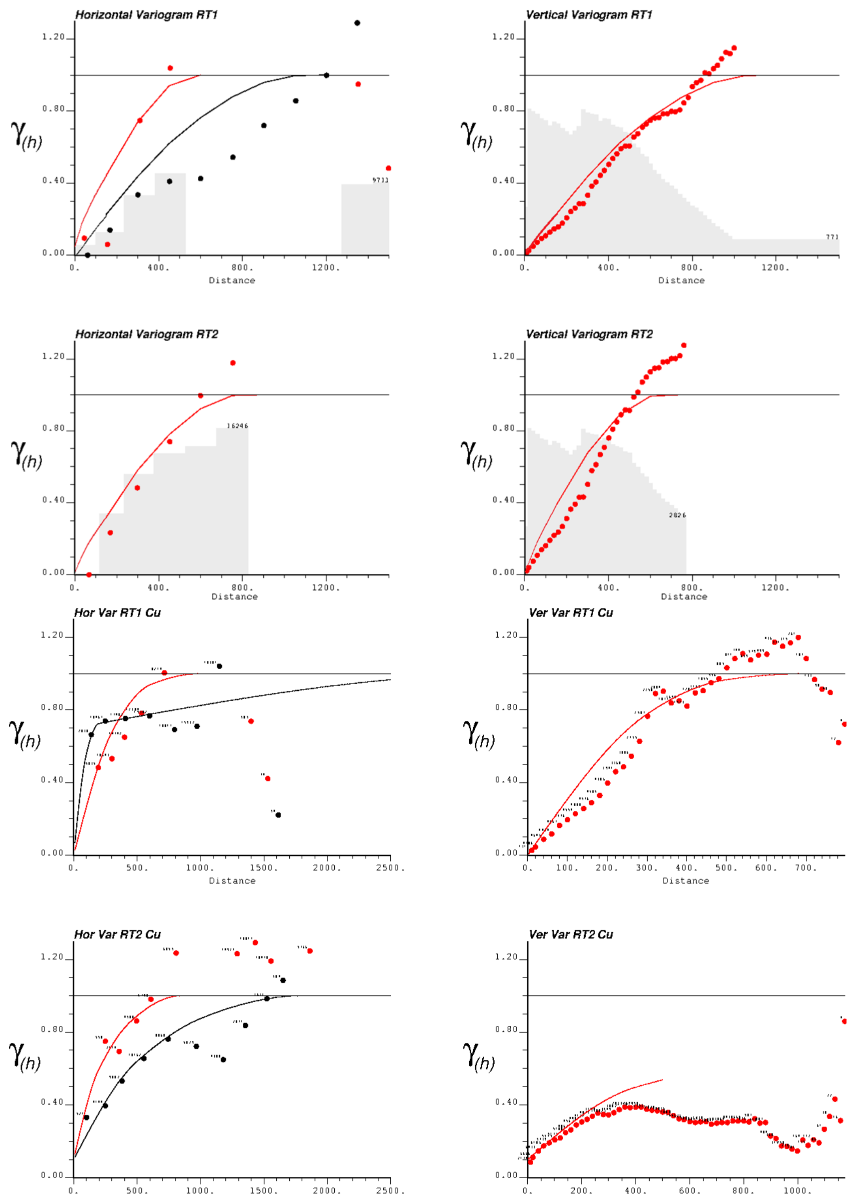


Fig 9. Four fitted Indicator variograms on the top, and four fitted continuous variograms at bottom

5. Sequential Gaussian Simulation

Besides the deterministic implicit modeling of rock types that has been performed and shown at the beginning of this paper, a rock modeling of sequential indicator simulation(SIS) has been conducted (Figure 11, on left). The SIS model is used to regulate the continuous data in order to generate forty simulated realizations with the software of sequential Gaussian simulation of the GSLIB catalog (Deutsch and Journel, 1998). Then; forty realizations are performed to obtain the input values for PCBC. These simulated realizations are considered to be equally probable. The process to perform the SGS is explained briefly as follow:

1. Determination of the correct grid is defined; it will be according to the horizontal and vertical continuity. A total of 1210000 blocks make the model framework. The grid

dimensions are of 20 meters in X axis, 20 meters in Y, and 15 meters in Z. The origin of coordinates is: X = 600m, Y = 100m and Z=600m.

2. After declustering and normalization, data is used as the main input within the sequential Gaussian simulation software of the GSLIB catalog (Deutsch and Journel, 1998).
3. To generate multiple conditional realizations of the main variable (Cu) within the Sequential Gaussian Simulation software (sgsim), a variogram model is needed. It is worth to mention that, the sgsim software is one of the most commonly applied geostatistical simulation algorithm that is used in the mining sector. Fig 10 illustrates two plots of realizations that are performed at level 1150; they are samples of the SIS model and the SGS model respectively. They both belong to realization 1, slice 74 (level 1150).
4. To validate the reproducibility of the SGS model, the reproduction of histograms is performed (Fig 11). Results display a good reproduction for domain 1 (intrusive). However, domain 2 shows an acceptable reproducibility, but it is not as good as domain 1. This is happening probably because the boundary is soft, and the mean and variance of the reference original data seems to be affected by some of the high copper values.

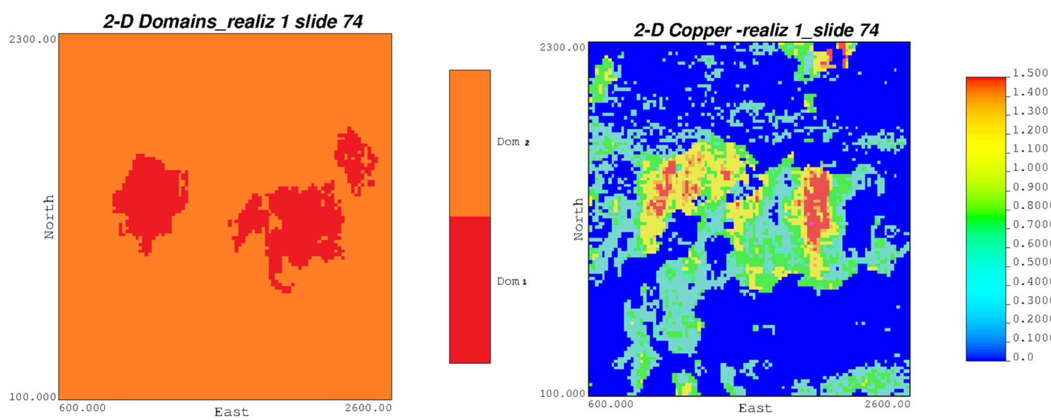


Fig 10. A SIS realization (left) and a SGS realization (right). They both belong to realization 1; slice 70 at the 1110 level

6. Setting the PCBC Parameters and the Transfer Function

After the geostatistical simulation modeling is performed, and a group of forty realizations are obtained, the setting of the transfer function is started. These realizations are considered to be equally probable block models of copper. Then they have been imported to a mining software, called Gems. To process these forty realizations inside the PCBC module, several mining assumptions and parameters need to be considered. Tables 2 and 3 show the essential assumptions and parameters that need to be taken into account inside PCBC before any calculation is made.

The imported copper models are manipulated in Gems. Then, additional values such as rock, density and percent of fines are added to these models. Once the 40 block model is completely ready to be used, the PCBC module is set. It is important to mention that some assumptions are made based on previous studies and the authors' experience, look at Table 3.

The PCBC journey begins with the setting of some assumptions. The first assumption is taken from the averaged fragment size, where rock is moderately fractured. Then the average size is assumed to be 0.5-1 m^3.

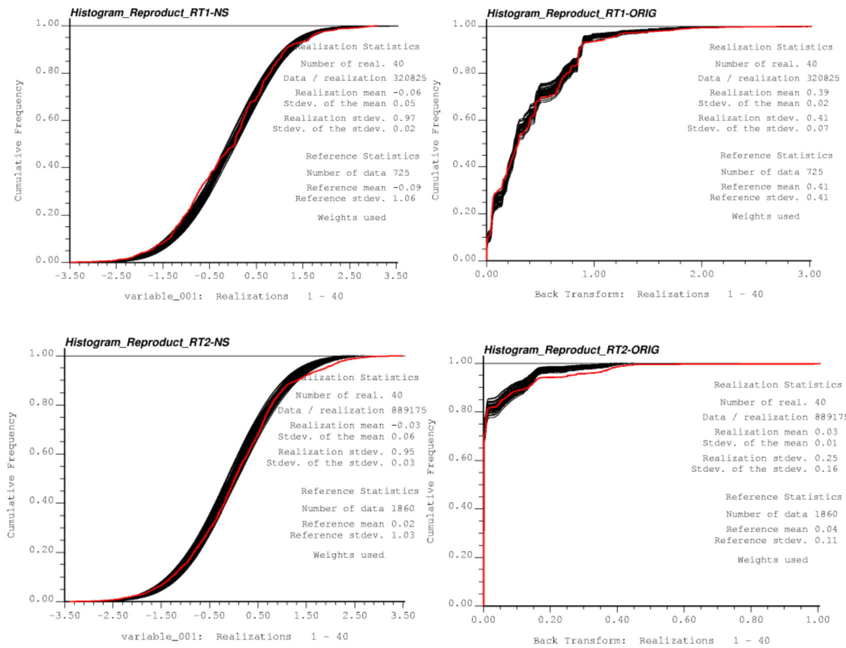


Fig 11. Histogram reproductions for Domain 1 and Domain 2, for the original and NS data

Table 2. Three drawpoint layouts used to find the optimal net value

Layout type (Herringbone)	spacing across major pillar (m)	spacing across minor pillar (m)	Description
20×10	20	10	The distance between drawpoints within same bell is 10m
20×15	20	15	
20×20	20	20	

Table 3. Relevant mining parameters and assumptions used within PCBC

Parameters & Assumptions	Value	Units	Description	References
% of Fines (ore&waste)	30	%	Based on a model of fines	Diering, T., (2013)
Density	2.5	kg/cm3	Average density for the orebody	Authors (2016)
HIZ	100	m	Height for interaction zone	Diering, T., (2013)
Swell factor	1.2	-	Stablish by experience	Authors (2016)
HOD_MAX	500	m	Maximum Height of Development	Diering, T., (2000)
HOD_MIN	30	m	Minimum Height of Development	Diering, T., (2000)
Discount Rate	0	%	It is assumed 0 % discount rate	Authors (2016)
Initial Elevation	1150	m	Initial Elevation of extraction	Geovia-Footprint Finder
radius of drawcone	5	m	Based on fragment sizes	Laubscher, D (1994),
layout type	-	H	Herringbone type	Ahmed, H. et al., (2014).

Consequently, the radius of the drawcones should be set to 5 meters. After that, the second assumption that needs to be considered is the initial level of extraction which is assumed to be 1150m. It worth to mention that, the extraction level has been obtained previously by running the "Footprint Finder" located amid the tools of PCBC-Gems. The assumptions and the main variables are essential for starting with the calculation of the responses within PCBC as well as other parameters that need to be completed to guarantee the successful usage of the transfer function into the PCBC module.

After the previous delineation of the initial footprint level, a number of sensitivity studies are performed. Therefore, a narrowed number of extraction layouts have been elected; In addition, a summary of other assumptions and parameters is made. In addition, the information of development cost for the extraction layouts is shown in the Fig 12 and the Table 4. The herringbone layout type that is used throughout the entire study.

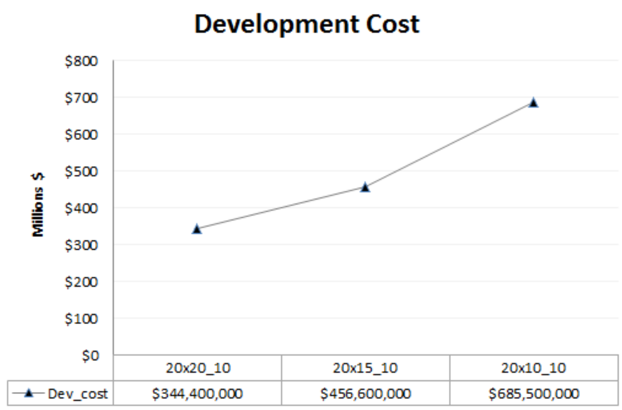


Fig 12. The development cost for the three extraction layouts

Table 4. Mining and development cost for the three extraction layouts

Block Caving Layout(Herringbone)	Mining Cost ($/tonne)	# of Drawpoints	Development Cost ($/drawpoint)	Total development Cost ($M)
20×20	7.0	2296	150,000	344.4
20×15	9.3	3044	150,000	456.6
20×10	13.9	4570	150,000	685.5

7. The Optimal Drawpoint Spacing within the Initial Footprint

The PCBC-Gems module does not only allow a numerical model to be set up, but also allows the columns above the drawbells to compute the minable reserves (Fig 13) in a variety of scenarios. Each extraction layout is one different scenario (Table 2). In this study, the PCBC generates 40 different responses for each of the three scenarios, and the final results that is evaluated in this paper are in terms net value ($). The main idea is to run each of the 40 realizations by three times. These three times represent the three different drawpoint spacing that is shown in Table 2 and Table 4. They are 20×10, 20×15, and 20×20. In other words, the 40 realizations obtained from the previous simulation are used in PCBC to determine 40 response variables for the three types of extraction layouts.

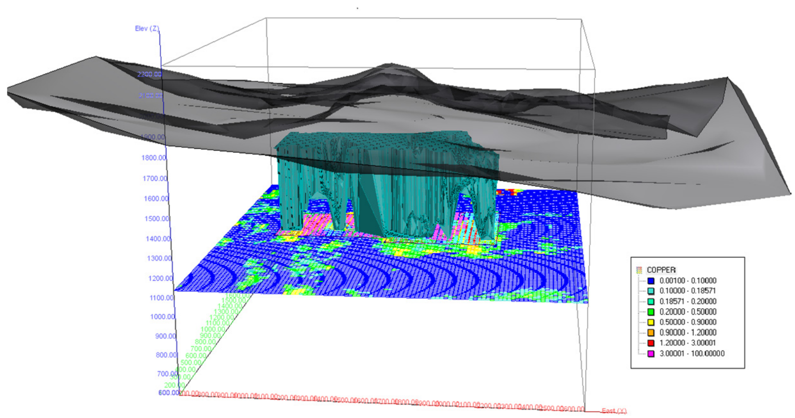


Fig 13. Calculation of minable reserves by PCBC. The optimal drawpoint layout and the best level possible are shown in here.

Fig 14 illustrates the response variables for these three scenarios, 20×10, 20×15, and 20×20. These response variables are plotted on the left side of Fig 14, where three distributions are shown in terms of net value ($M). Notice that the averaged net value obtained from the distribution at layout "20×15" seems to be the optimal one. Furthermore, the right side of Fig 14 shows a ranking of the best values for each layout. 88 % of the maximum values are obtained for layout "20×15". It is worth to mention that; further uncertainty assessment can be performed with this data.

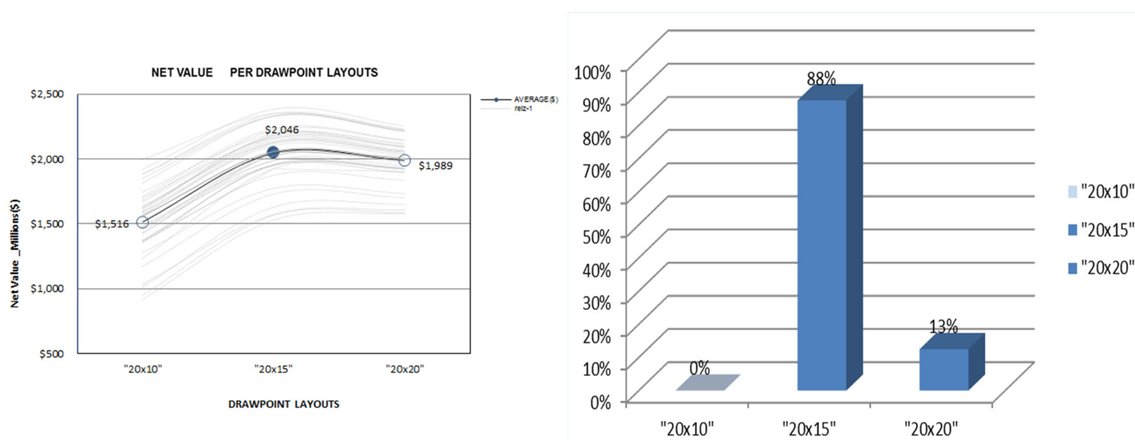


Fig 14. On the left, the forty net values for the 3 layouts, and the ranking of best results on the right

Fig 15 shows a histogram of the distribution at layout "20×15" which appears to present the most optimal net value; the mean net value is around 2046 million with a standard deviation of 218.

8. The Best Level of Extraction Based on the Optimal Drawpoint Spacing

Once the optimal drawpoint spacing is completed, a complementary evaluation of the best extraction level is made with PCBC- Gems. The layout “20×15”, now, is used to find the best elevation of extraction. Then, this level of extraction will be used in a second round of the optimization process. In fact, only one round has been shown in this paper. To find the best level of extraction based on the optimal drawpoint spacing, an evaluation is conducted within the following four elevations: 1030 m, 1090 m, 1150 m, and 1180 m.

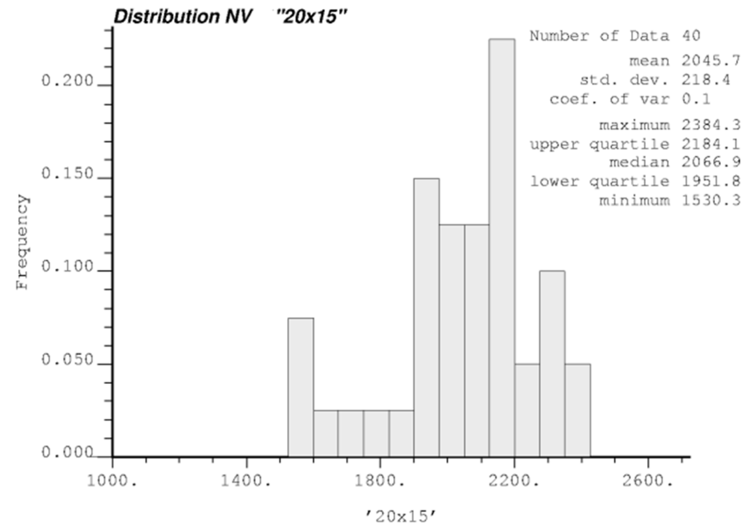


Fig 15. The distribution of the net values ($M) for the optimal extraction layout

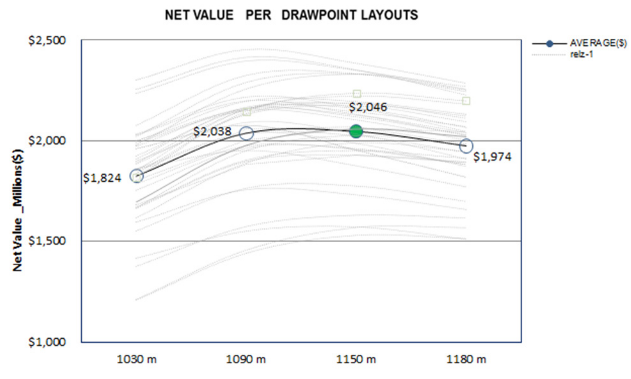
These elevations are chosen arbitrarily based on the author's experience. However, the ideal elevation should be proportional to the block sizes.

In the left side of Fig 16 is shown the results of the calculation performed in PCBC-Gems where the best average of the net values appears to be at the elevation 1150 m. Around 55% of the best responses (net values) are at elevation 1150 m. However, 45% of best net values are at elevation 1090 m; this ranking of results is illustrated on the right of Fig 16. Furthermore, Fig 17 shows a histogram of the distribution at elevation 1150 m performed in the optimal layout; the mean net value is around $2046 M with a standard deviation of 218.

9. Results and Discussion

Among the three layouts which were evaluated in this study, the "20×15" appears to show the optimal net value; the mean of the net values is around $2046M with a standard deviation of 218. We need to remember that the initial evaluation within PCBC-Gems is performed at an extraction level (footprint), and It is relevant to mention that this initial extraction level has been obtained automatically by running the Footprint Finder of the PCBC-Gems. The methodology of this paper also proposed a complementary evaluation of the best level of extraction using all realizations; in this case, the optimal drawpoint spacing needs to be fixed. From the response results of the calculation performed in PCBC-Gems, the best average of the net values appears to be at the elevation 1150 m with 55% of best responses (net values) in where the mean net value is around $2046M with a standard deviation of 218.

The study results demonstrate that the SGS is useful to obtain an optimal drawpoint spacing based on realizations. This paper certainly explains, in simple steps, how to generate the best possible drawpoint spacing for a specific "extraction layout" of a block caving mine. It is also explained here, the results of additional evaluation to obtain the best level of extraction using a fixed drawpoint spacing. In other words, given the drawpoint layout of "20×15" as the optimal drawpoint spacing at the initial level of extraction, a complementary evaluation of elevation is performed. This new elevation would be used to perform further optimization of the drawpoint spacing following the previous steps.



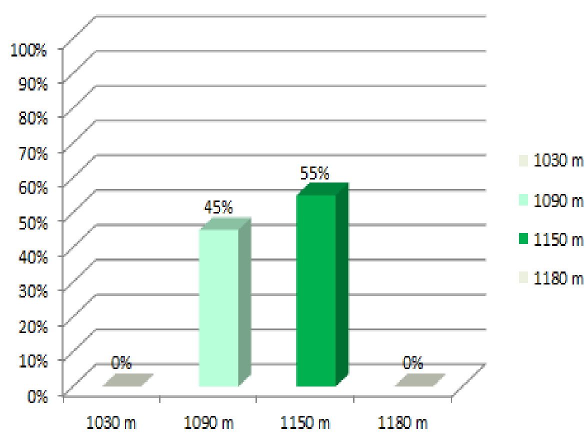


Fig 16. Responses of net value for the forty realization, and the ranking of results for the four levels

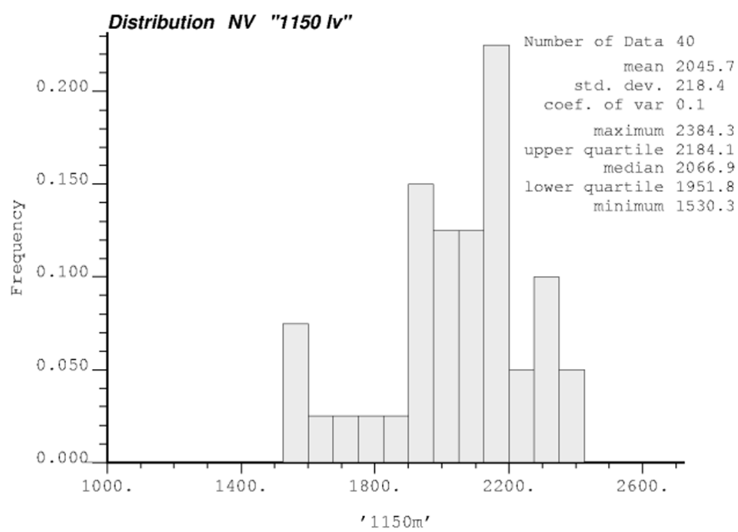


Fig 17. Histogram with the distribution of the net values ($M) for the best elevation of extraction

10. Conclusion

Overall, the optimal drawpoint spacing within the extraction level will help to achieve the production targets of a mine. For instance, tonnage, grade, and consequently the profit of the block-cave mine. As explained in the introduction, this type of mining is undeniably complex since they depend on several assumptions and parameters related to their geological and technical constraints.

However, there are few essential features that need to be considered carefully because this work illustrates a completely new approach to solve one of the trickiest features of block caving. In fact, this paper is opening a discussion about a new application for simulation in the mining context, using "all realizations all the time". This paper explains also a comprehensive workflow to maximize the profitability of the block caving mines. The maximization of the profit would be based on the optimal drawpoint spacing within the best level of extraction. Nonetheless, further complementary studies of geostatistical simulation and uncertainty assessments should be done for block caving, in the future.

11. References

[1]. Ahmed, H. M., Scoble, M. J., & Dunbar S. (2014). A comparison between Offset Herringbone and El Teniente underground cave mining extraction layouts using a discrete event simulation technique. *International Journal Journal of Mining Reclamation and Environment 30*(2):1-21.

[2]. Castro, R, Vargas, R & Huerta F (2012). Determination of drawpoint spacing in panel caving: a case study at El Teniente Mine. *The Journal of the southern African Institute of Mining and Metallurgy, vol. 112.*

[3]. Deutsch, C. V., & Journel, A. G. (1998). GSLIB: Geostatistical Software Library and User's Guide (2nd ed.). New York, NY: Oxford University Press.

[4]. Deutsch, C. V. (2015). All Realizations All the Time, CCG Paper 2015-101, Centre for Computational Geostatistics, University of Alberta, Edmonton, Canada

[5]. Diering, T., (2000). PC-BC: A block cave design and draw control system. *Proceedings MassMin,* Chilean Engineering Institute: Santiago, Chile, pp.469-484.

[6]. Diering, T., (2013). PC-BC: Reserve estimation using GEOVIA PCBC. Dessault Systemes Geovia Inc. Vancouver. British Columbia, Canada.

[7]. Laubscher, D (1994): Cave mining-the state of the art, *Journal of the South African Institute of Mining and Metallurgy*, pp. 279-293.

[8]. Laubscher, D.H. (2000): Block Caving Manual, prepared for International Caving Study, JKMRC and Itasca Consulting Group, Inc.