Optimal open-pit short-term planning under uncertainty and blending constraints

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ABSTRACT

Short-term mine planning is a key point in the mining business, because it is when the profit promise of long-term plans is done. Despite that, most of the efforts in developing mathematical models and techniques are spent in long-term models whose output are based on many additional information and simplified constraints. This means that the short-term planner must deal with a lot more variability in the data and meet constraints that were not taken into account when constructing the long-term plan. This often means that in order to satisfy the production goals, imposed by the long-term plan, the short-term planner must either make changes in the exploitation sequence, affecting future production, or incur in higher costs.

The aim of the study presented in this paper is to generate a tool considering such variables, allowing for the generation of multiple decision scenarios done in a reasonable time, and providing a guide for the mine planner, for short and medium term horizons. The focus of the model are the blending constraints related to the geometallurgical attributes of the ore sent to the processing plant, but it also considers the dynamics of stocks, geometrical constraints, plant and mine capacity, among others, in order to determine a sequence of exploitation and processing such that the overall ore production is maximised. It also includes the possibility to analyse mine operation design selectivity using different loading and haulage equipments, according to the study of different basic clustering blocks units.

The tool was implemented and applied at the BHP Billiton Spence mine, located in the north of Chile, in order to obtain a plan for the quarter September-November of 2008 and the year July 2009-July 2010. The results correspond to probability maps for the extraction period of each block, graphical analysis of the reliability of production goal, and modelling of relations between clustering unit sizes and the selectivity and functionality of the mine design.

INTRODUCTION

Mine planning is defined as the process of mining engineering in charge of transforming the mineral resource into the best productive business, while a production schedule is a productive promise that corresponds to a bankable document for investors [15]. Therefore, mine planning aims to determine which part of the resource must be extracted in each period in order to maximise profits from mineral processing, including decisions such as which part of the resource must be processed, the required investment for the plant and hauling equipments requirements, among others.

Currently, mine planning process is made considering operational and metallurgical constraints, building short and medium term mining plans through manual approaches of trial and error with an important time investment to generate a result which no one absolutely knows if is the right option which maximises the business in terms of recoverable metal, fleet utilisation and reserves consumption among other items, since it is extremely difficult to include ore variability in the production schedule using the available traditional software.

In consequence, the main decisions concerning Life of the Mine (LOM) are considered first, once given these, further decisions are taken into account in relation to long term (10 to 30 years depending on the deposit). Then, considering as fixed the results previously obtained, it is necessary to develop plans for the medium term (usually up to five years) and so on till the daily detail, going through the annual planning which compromises directly the operational budget. This dismembered analysis structure leads to a massive scale mine exploitation, with large equipment and high production rates, without taking into account that mineralogical variability of the body to be exploited may require a greater selectivity degree in the extraction, ultimately leading to significant discrepancies between long and short term (where it faces the real mineral variability) incurring significant cost increases in order to achieve production goals involved.

RELATED WORK

Large open pit mine operation and administration is a huge and complex task, particularly for older mines. Optimisation techniques can be applied successfully to resolution of important issues that arise in mine planning and management. These applications include: ore body modelling and reserves estimation; optimal pit design, determination of optimal production schedules, determination of optimal operational design, determination of optimal mixtures, equipment maintenance time determination, equipment replacement policies, and several others [3].

Mine planning process

In general terms, mine planning process can be divided into different levels according to the characteristics of the decisions [1]:

- Strategic: Refers to exploitation methods choices, mining and processing capacity and overall mineral reserve estimates. The main goal of strategic planning is to synchronise the market with the available resources and the company's mission statement.
- Tactic: It corresponds to processes specifications to make over the life of the mine, such as long term production schedules and the use of equipment and processing plants inside the mine. Tactic or conceptual planning determines how to achieve the target set earlier by strategic planning. The result is the mining plan, which defines how and when resources are extracted in each period of the mining business.

- Operating: They are daily made, for example, trucks address dispatching. Within the operational planning, processes and operational rates resulting from the mining plan are included. Here, the conceptual planning feedback takes place.

The strategic decision of determining the optimum final pit has been effectively treated using the Lerchs-Grossman algorithm [10] or the Picard flow networks method [13] (see also [2, 4]). These methods are based on a block model which characterises a mineralised body. Moreover, the problem of generating a production schedule can be defined specifically as the sequence in which blocks should be removed from the mine with the objective of maximising the total profit, defined according to the company strategic goals, subject to a series of physical and economic constraints. This problem can be formulated using integer linear programming, however in real applications, this formulation is too extended, both in terms of number of variables and number of constraints to be solved with available MILP software. In consequence, it appears the necessity to divide the problem, first establishing a final pit, and then sequencing the blocks contained in it.

A number of approaches for solving the sequencing and scheduling issue in the extraction of blocks have appeared in the literature, including: heuristic [2, 8]; relaxation lagrangean; parametric methods [5, 11, 15, 16], mixed integer linear programming [3, 4, 8]; and the application of artificial intelligence algorithms such as genetic algorithms and neural networks [6]. Due to the complexity and size of the problem, all these approaches suffer from one or more of the following limitations: Is not possible to cover most of the constraints that arise, deliver sub-optimal solutions without a quality measure in most cases and they can only address problems of limited size. Smith [15] notes that while long-term planning is typically responsible for maximising the project value, short-term planning is commonly associated with a target based on production goals with maximum or minimum limits of certain chemical constituents critical such as in mining coal with high sulfur content, where the maximisation of sulfides production is considered. Smith [15] poses a mixed integer programming model which is responsible for blocks scheduling extraction in the short term, with the objective of maximising the production of material of interest, subject to certain constraints on blending, while ensuring a simple scheme of horizontal and vertical constraints without considering the presence of stocks. In the same line Camilo Morales [18], presents a model to maximise the production of metal in a copper mine, subject to certain geometallurgical constraints.

Clustering

Aggregation mechanisms combined with optimal solution strategies have also begun to play a role in block sequencing for the short-term. Specifically, the authors try to reduce the model size by combining blocks with similar properties. Ramazan [13] proposed an aggregation scheme that uses linear programming to construct 'fundamental trees' to reduce the number of blocks (entities) to be sequenced. After performing this aggregation, the general problem of block sequencing can be solved, but now with far fewer variables because of aggregation. The author applies his techniques to a mine of about 40,000 blocks to be extracted for eight years. Boland *et al.* [19] uses binary variables to meet precedences between blocks clusters, while continuous variables control the amount of material removed of each cluster, as of each block in an aggregate. The authors demonstrate their procedure using cases that contain up to 125 macro-blocks aggregates in a model of nearly 100,000 units. The times for a 1% solution close to the optimum, vary between thousands and tens of thousands of seconds.

OPTIMISATION MODEL

The mathematical model that aims to deliver a guide for building short and medium term plans, using a general outline of destinations and attributes for each block for copper mining will be described as follows in this chapter. In relation to the destinations, it works on the basis that from a copper mine, five main types of materials are extracted, which are: sulphides, oxides, mixed, sterile and ROM. It also adds the chance of differentiate in campaigns the extracting of different minerals lithologies and the stocks presence.

Clustering Tool

An obvious way to reduce the number of variables to solve the optimisation model is to select block groups and add them in order to obtain a final model that now includes macro-blocks. Traditionally, this aggregation is done generating clusters of regular dimensions (see Figure 1), for example, from blocks dimension of 10x10x10 to macro-blocks of 30x30x30 where each macro-block containing 27 (33) of the original blocks, attributes as grades or pollutant contents are averaged to obtain the final value for the macro-block. This way of clustering blocks is useful and efficient for porphyry ore bodies, where large volume of material with identical mineralogical characteristics distributed uniformly but for ore bodies with chaotic nature in regard to the lithologies spatial distribution, this might not be the right thing.

Given the need for a mechanism able to make a smart clustering, using as a programming platform Python language, a tool capable of receiving a block model and giving a set of macro-blocks was developed. These macro-blocks, hence MRU (operational unit resources) are the result of clustering blocks according to a function defined for convenience, being also possible to intercept different types of aggregations, for example, in the case of ore bodies with high mineralogical variability, is possible to generate macro-blocks due to the interception of a regular clustering (30x30x30) with a clustering by the attribute lithology (see Figure 2).

This method of aggregation generates a group of irregular macro-blocks creating the necessity of implementing tools that could work properly, particularly in the definition of vertical and horizontal precedences and extraction progress control from the access.

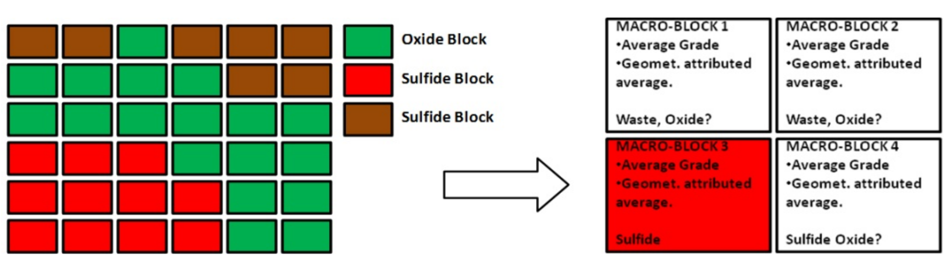


Figure 1 Clustering traditional methodology

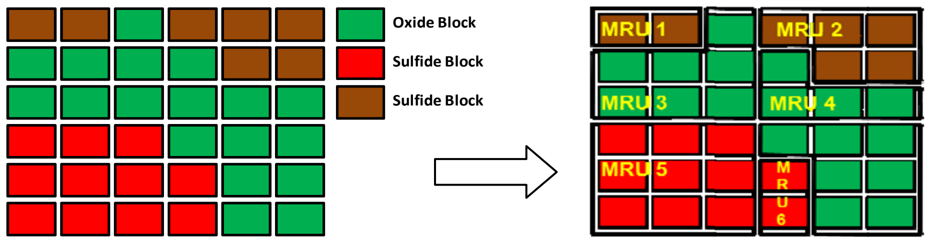


Figure 2 Generated clustering tool

Implementation of graph structure

Given the new scenario, which must be capable of handling irregular macro-blocks (MRU), it is necessary to connect the spatial arrangement of these MRU through a graph, in which a node is directly associated with a MRU and the vertices to the connections generated within a radius of neighbours of each MRU (node).

By having each level of the model characterised by a connected graph, we can calculate the minimum distance from road access to each MRU, which allows the determination of the precedent MRU for each MRU.

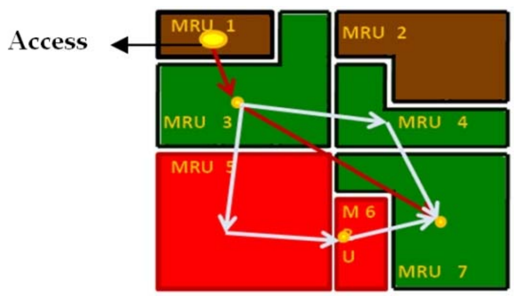


Figure 3 Minimum path between two MRU

As an example, Figure 3 considering that the MRU 1 corresponds to an access, the minimum distance path from the entrance to the MRU 7 is: MRU 1 - MRU 3 - MRU 7, indicating that the MRU 7 is preceded by MRU3 and MRU 3 by MRU 1 respectively.

Input and model parameters

The optimisation model requires as input a block model in which each block has a spatial location (coordinates) and well-defined attributes, table 1 lists these attributes and a brief description of them.

Each block has a tonnage ton($\bar{u}$), destination dest($\bar{u}$) ϵ (OX, SP, ROM, WST) and a set of A geometallurgical attributes for each block: g($\bar{u}$, a) for a = [1, ..., A]. The same attributes are required for either oxides and sulphides stocks g(OX, a), g(SP, a) for a = [1, ..., A]. Finally, ROM blocks are always processed on a different line than in the case of oxides and sulphides.

Table 1 General model notation

Symbol	Meaning
B	Set of blocks
$\bar{u}$	Block coordinates
T	Time horizon (number of periods).
t	Time period ($t \in \{1,2,\dots,T\}$)
OX, SP, ROM, WST	Block destination (Oxides, sulfides, ROM or waste line processing)
A	Block model sets (*e.g.* geometallurgical)
a	Block model Attribute
$CU(\bar{u})$	Copper content in the block
$ton(\bar{u})$	Block tonnage

The model requires maximum capacity of plant and mine for every period. On the other hand, for each attribute, the average range that should be maintained for the processed blocks must be specified. If we consider time periods 1, 2, ..., T, then the mining and processing capacities will be identified as P(t) and M(t), and the maximum average value of each attribute as Ma for a = [1, ..., A]. Each time period is also labelled as sulphur or oxide, depending on the campaign to which it corresponds.

The extraction control from an access is obtained by incorporating the T_L parameter, which corresponds to the number of periods to extract a MRU account after having removed the previous MRU. In addition to that, the FMM parameter (mine movement factor) is set, which allow saturating the hauling capacity.

Variables

Regarding the model blocks, two sets of variables are considered, one for mining and the other for processing. The first set determines when a block is extracted from the mine. For a block U and t = [1, ..., T], where:

$$m_{\bar{u},t} = \begin{cases} 1 & \bar{u} \text{ block is extracted in } 1..t \\ 0 & \text{other case} \end{cases}$$

The second set determines when a particular block is processed:

$$p_{\bar{u},t} = \begin{cases} 1 & \bar{u} \text{ block is processed in } 1 \dots t \\ 0 & \text{other case} \end{cases}$$

Similarly are denoted as p(OX, t) and p(SP; t), the number of processed blocks from the stock of oxides and sulphur respectively in period t.

To simplify the writing of the model, it is useful to introduce some auxiliary variables relating to mine and process variables:

$$\Delta m(\bar{u},t) = \begin{cases} m(\bar{u},t) - m(\bar{u},t-1) \text{ si } t > 1 \\ m(\bar{u},1) \text{ si } t = 1 \end{cases}$$

$$\Delta p(\bar{u},t) = \begin{cases} p(\bar{u},t) - p(\bar{u},t-1) \text{ si } t > 1 \\ p(\bar{u},1) \text{ si } t = 1 \end{cases}$$

Δ variables have the advantage of having a rather simple interpretation, for example $\Delta m(\bar{u}, t)$ is equal to 1 where a block (ū) is mined in exactly the period t.

Objective function

Each block has a copper content CU (ū) as an attribute. We want to maximise the amount of metal produced in the horizon of T time periods involved in the problem. Only sulphide and oxide blocks are considered in the objective function because these are the main sources of copper.

$$FO: \sum_{\text{dest}(\bar{u})\, \epsilon\, \{OX,SP,ROM\}} \sum_{t=1}^{T} CU(\bar{u})\, \Delta p(\bar{u},t)$$

Constrains

The blocks can be mined and processed only once:

$$m(\bar{u},t) \leq m(\bar{u},t+1), \quad 1 \leq t \leq T-1 \tag{1}$$

$$p(\bar{u},t) \leq p(\bar{u},t+1), \quad 1 \leq t \leq T-1 \tag{2}$$

Only mined blocks can be processed:

$$p(\bar{u},t) \leq m(\bar{u},t+1), \quad 1 \leq t \leq T \tag{3}$$

Stocks are limited:

$$\sum_{t=1}^{T} p(OX,s) \leq N(OX) \tag{4}$$

$$\sum_{t=1}^{T} p(SP,s) \leq N(SP) \tag{5}$$

Capacities: Both the mine capacity and processing capacity at the plant must be respected. For any t = [1...T]:

$$\sum_{\bar{u}} \mathrm{ton}\,(\bar{u})\Delta m(\bar{u},t) + \mathrm{ton}(OX)p(OX,t) + \mathrm{ton}(SP)p(SP,t) \le M(t) \tag{6}$$

$$\sum_{\bar{u}} \mathrm{ton}\,(\bar{u})\Delta p(\bar{u},t) + \mathrm{ton}(OX)p(OX,t) + \mathrm{ton}(SP)p(SP,t) \le P(t) \tag{7}$$

Vertical precedences: Previous blocks to a given target block, should be removed, that is, for each ($\bar{u}_1$, $\bar{u}_2$) ϵ Γ (set of arcs in the precedence graph for a given angle of slope) and t = [1, ...,T].

$$m(\bar{u}_1,t) \le m(\bar{u}_2,t) \tag{8}$$

Horizontal Precedence: This restriction require that once a block is extracted in a period t, there is a TL limit of periods to extract the next block in the horizontal arc of precedence (see Figure 4), *ie*., for each ($\bar{u}_1$, $\bar{u}_2$) ϵ Π (set of arcs in the precedence graph horizontal) and t = [1...T].

$$1 - m(\bar{u}_1,t) \ \ge \ m(\bar{u}_2,t+T_L) - m(\bar{u}_2,t+T_L-1) \tag{9}$$

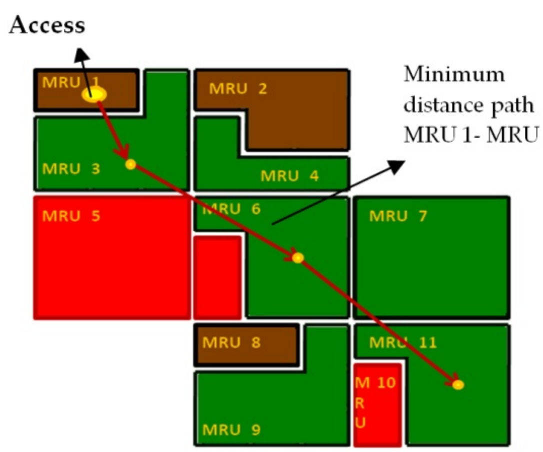


Figure 4 Horizontal precedence diagram

Campaigns: During an oxide campaign, there is no chance for sulphide blocks to be processed: For all t = [1, …, T] and ū such that dest (ū) = SP.

$$\Delta p(\bar{u},t) = 0 \tag{10}$$

$$p(SP,t) = 0 \tag{11}$$

Similarly, during a sulphide campaign, then neither oxide blocks nor blocks from the oxide stock are processed: For all t = [1, …,T] and ū such that dest (ū) = OX.

$$\Delta p(\bar{u}, t) = 0 \tag{12}$$

$$p(OX, t) = 0 \tag{13}$$

Blending: For each blending attribute a= [1, …,A] we have a maximum average of M_a so:

$$\sum_{\bar{u}} g\,(\bar{u}, a)\Delta p(\bar{u}, t) + g(OX, a)p(OX, t) + g(SP, a)p(SP, t) \\ \leq M_a\,[\Delta p(\bar{u}, t) + p(OX, t) + p(SP, t)] \tag{14}$$

Transport capacity saturation: Because the graph structure and the definition of horizontal precedences that ensure the geometric connectedness of the solution, it is possible to add a constraint that ensures the saturation of the hauling capacity in the mine, for all t = [1,…,T]:

$$\sum_{\bar{u}} ton\,(\bar{u})\Delta m(\bar{u}, t) + \ ton(OX)p(OX, t) + \ ton(SP)p(SP, t) \ \geq FMM \cdot \ M(t) \tag{15}$$

Where the FMM parameter corresponds to a mine movement factor, where value fluctuates between 0 and 1.

Heuristics to reduce computation time

A sequencing problem is divided into periods, from the first (1), to the horizon (T). In general, it is observed for a universe of fixed blocks, the difficulty of solving a sequencing problem increases dramatically with the number of periods T. It is natural then to search for decomposition resolution schemes in order to maintain the T value bounded. A possible technique to use is a pattern of 'windows', which resolves the problem of sequencing for the first T'<T periods, then this firsts periods are fixed as part of the solution and then the technique continues solving for the following non fixed T' periods in an iterative way until the entire horizon have been solved, as seen in the Figure 5.

This mechanism was successfully applied in the optimisation model described above, achieving a significant reduction in computation time, verifying that, for certain window sizes, feasible solutions are obtained with a gap of no more than 5% with a computation time about 80% lower to those for solving the problem without this scheme. This reduction in computation time can make the leap to analyse uncertainty associated with mine planning process, incorporating into the production schedule calculation, geostatistical simulations of the resource model.

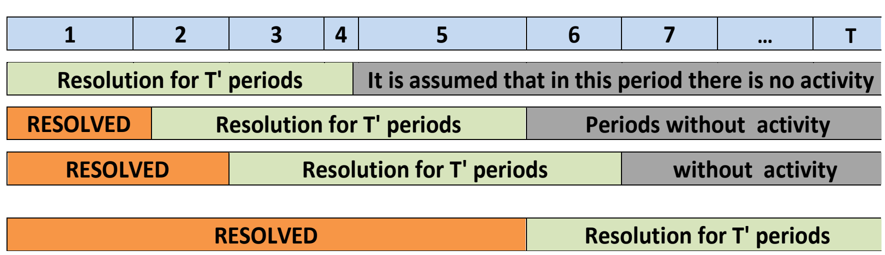


Figure 5 Time-Frame Methodology

RESULTS

The model was tested both for a short (Quarter) and medium (Forecast) time horizon, using data from Spence mine, owned by BHP Billiton. For the first case, the data used are those for the quarter July to September 2008 and for the second one from fiscal year July 2008 - July 2009.

The issue presented in this study was solved using an integer programming model, whose implementation was done using the AMPL programming language, and whose resolution was made using the commercial software ILOG CPLEX, version 10.2.

Spence Mining Company

The Spence mine is a company 100% BHP Billiton owned. The mine operation is located near the community of Sierra Gorda in Region II of Northern Chile, approximately 50 km southwest of Calama and 150 km northeast of Antofagasta.

In geological terms, it corresponds to a supergene enriched and partially oxidized porphyry copper deposit from Upper Paleocene age (~ 57 M Years), 100% covered by gravels with mineralisation depth ranges from 80 to 100 metres below surface, where the supergene sulphide and the oxide mineralisation are associated with the presence of atacamite and chalcocite respectively. Five types of materials are drawn from the mine, which are: sulphides, oxides, mixed, ROM and waste, those which are classified agree to characteristics of the block model.

The operation is conducted through an open pit mine with leaching and SX-EW (Solvent extraction/Electro winning) production facilities, with a mining rate ex-pit up to 260,000 tonnes/day and an ore treatment rate of 50,000 tonnes/day for an approximate nominal annual production capacity of 200,000 tonnes copper cathode. Finally, the cathodes are carried to either ports of Antofagasta or Mejillones for shipping to customers.

Geometallurgical constraints

The processing plant imposes certain geo-metallurgical constraints to obtain final copper cathode with maximum recovery, ensuring maximum efficiency step in the process. The constraints that must be met are:

Table 2 Geometallurgical Constraints

Attribute	Upper limit
CO3	0.8 kg/t
Clacid	0.8 %
Blend	25 %
F_Geomet	20 %

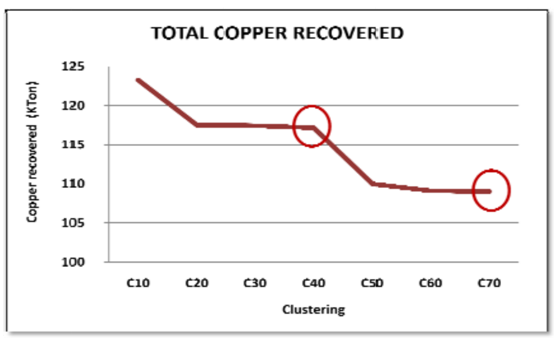
Quarter Spence Application

It was worked with the block model for the period between July and September 2008, which has a total of 9,976 blocks of 10 x 10 x 15 metres size. Model exploitation was roughly divided into two weeks period (see Table 4), with certain exceptions such as when there is a change of campaign or when days of the last week are less than the 14 required. The mathematical model considers the use of two stocks, sulphides and oxides respectively, and its objective function is to maximise the tonnage of copper recovered.

Table 3 Resolution parameters

Period	Days	Campaign	LIMITS Mine (Kt)	Plant (Kt)	Clacid (Kg/t)	CO3 (%)	F_Geomet (%)	Blend (%)
1	14	Sulphides	3,080	700	0.8	1.2	20	25
2	14	Sulphides	3,080	700	0.8	1.2	20	25
3	14	Sulphides	3,080	700	0.8	1.2	20	25
4	14	Sulphides	3,080	700	0.8	1.2	20	25
5	14	Sulphides	3,080	700	0.8	1.2	20	25
6	7	Sulphides	1,540	350	0.8	1.2	20	25
7	14	Oxides	3,080	700	-	1.2	20	25
8	1	Oxides	220	50	-	1.2	20	25

Depending on mine and plant capacities presented in Table 4, saturation of the transport capacity of 95% is imposed (Equation 15). Finally, a slope angle of 50% (Equation 8) and a value of $T_L = 2$ (Equation 9) are established, the latter parameter as explained above corresponds to the maximum time to extract a block on a path of minimum distance, after having extracted its previously.



Graph 1 Copper recovered by level of aggregation

The mathematical model was solved in an Intel® Xeon® 1.6 GHz CPU and 3 GB of RAM notebook. Both, the geometrical results obtained for a representative bank visible in Figure 5 and the model calculation times vary depending on the size and shape of the selected MRU, the latter varies from 10 minutes without using any kind of aggregation till 10 seconds for a square aggregation of 60 x 60 x 15 intercepted with MintType and Phase-Bank attributes.

The objective function without using any kind of aggregation reaches a value of 124, 112 copper tonnes. The relationship analysis between the MRU selected (see Graph 1), copper recovery and geometric coherence of the resulting solution, throws that by growing the size of the MRU, copper recovery decreases, which is intuitively justified due to loss of selectivity associated with the use of basic operating units of larger size, but on the other hand, solutions corresponding to big clusters, look far more operational than those that do not use blocks cluster (see Figure 6). The nomenclature of aggregation in this work represents an square aggregation CX0 where, for example, X = 4 means that macro-blocks of 40 x 40 m^2 with target attributes, phase and bench of the block model are intercepted.

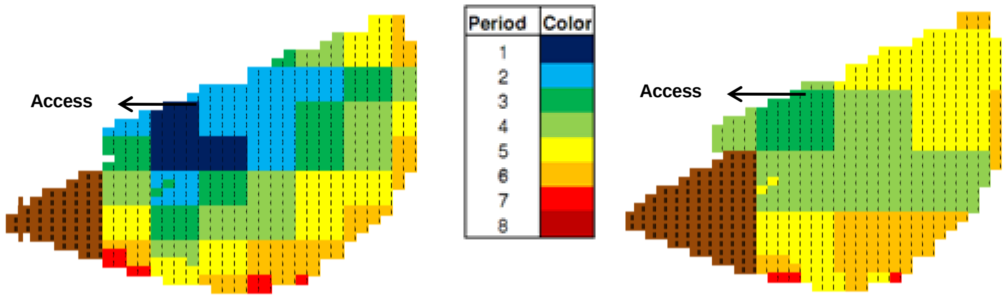


Figure 6 Geometric results for Phase 2-Bank 1580 with C40 (left) and C70 (right) clustering

CONCLUSIONS

Implementing a graph structure allows to define a pattern of vertical and horizontal precedence consistent with the logical order of blocks removal in the operation of an open pit mine. On the other hand, this restrictive scheme helps to reduce the range of feasible solutions, which combined with the use of an time-frame algorithm for ciplex resolution and the possibility of generate MRU, can both reduce the calculation times for a total of 14,000 blocks in about 97%, allowing to solve the problem in a personal computer at a time between 0.5 and 10 minutes depending on the level of aggregation.

Adding the concept of operating exploitation units (MRU) that feeds the optimisation model, not only allows to reduce significantly the model computation time and to address problems involving a larger number of variables, but also provides a tool for incorporating minimum operating areas for mining equipment, allowing analysis of the decrease or increase of the recovery associated with selectivity degree that can be achieved with a certain profile of mining equipment. The decrease in computation time and the use of MRU, allow address the problem of extract scheduling for a greater number of blocks (100,000 blocks).

FUTURE WORK

The implementation of the optimisation model described in this paper implies an important step to tackle the problem of uncertainty associated with the block sequencing problem for both the short and medium term, incorporating blending and operational constraints, this thanks to the drastic decrease in the calculation times. In this regard an important step goes in hand with the ability to add intelligent way, with the development of the tool described in this document. The challenges to address in the future are:

Improving resolution techniques: While in the model in its current stage, it is possible to deal with a universe of 100,000 blocks, in particular for those involved in the medium-term plan of Spence mine, still need to make significant improvements in algorithms resolution if it is wanted to address at some point the long-term problem.

To study changes in the objective function: The implementing a graph structure allows to incorporate the item of distances traveled to extract certain volume of blocks, this allows to aspire some changings in the objective function that incorporate the cost item in the model.

Build model with variables destinations: In its current stage, the model requires each block to have preset destination, this naturally affects the maximum value achieved by the objective function, an important challenge is to incorporate this item as a variable, so that the destiny of each block is the result of optimisation.

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