Design of Extraction Phases in Open Pit Mines Using a Genetic Algorithm

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ABSTRACT

The problem of open-pit mine planning has two components: a spatial component, which defines the extraction pushbacks, and a temporal component, which determines what is occurring at a certain time at the mine. The traditional methodology, based on nested pits, focuses on the spatial component while the direct block scheduling methodology focuses on the temporal component.

This work moves toward an integrated focus by defining volumes (phases), that respect typical selected operational conditions of the pit extraction, and the scheduling, that allows to reach the maximum NPV. A genetic algorithm was applied that allowed the generation of volumes to be accomplished with certain spatial conditions.

The genetic algorithm based the scheduling on the Constrained Pit Limit Problem (C-PIT), incorporating restrictions of operational design and geotechnical design, called (C-PIT +). Within the work, the different configurations were considered for the parameters of genetic algorithms, such as, population size and number of generations. The precedencies were resolved through a truncated cone, defined by its external angle, basal radius and base centre. The process of clustering cones truncated in pushbacks was done through the k-means algorithm.When comparing the results of the algorithm with the traditional approach, it was shown that it was possible to automatically generate volumes that are closer to operational designs and with higher NPVs.

INTRODUCTION

The main objective of mining is the transformation of a mineral resource into an economic benefit. In order for this transformation to occur several stages are necessary, which range from prospecting to commercialization. At the center of this process is the mine planning, which is responsible for defining a tentative production schedule which maximizes the value of the business.

The problem of open-pit mine planning has two components: a spatial component, which defines the extraction phases, and a temporal component that determines when to mine the resource. The traditional methodology, based on nested pits, focuses on the spatial component through the generation of pits to define certain phases that serve as the basis for the design and subsequent generation of a production schedule. The direct block scheduling methodology focuses on the temporal component and it seeks to define the ideal moment, in terms of NPV, for the extraction of a block, producing volumes that are associated with periods and a design, which is necessary to follow this sequence.

This work attempts an integrated approach, that is to say, to define volumes (phases) that respond to certain typical operational conditions of the open pit extraction and to create scheduling that allows to achieve the maximum values of NPV. This integrated approach is achieved through a genetic algorithm, which solves the problem of C-PIT, allowing the generation of volumes that comply with certain spatial conditions and creates a schedule with the aim to maximize NPV. In addition, this approach uses a truncated cone to comply with the slope angle and geotechnical constraints. The results of the scheduling and NPV obtained by this integrated methodology are compared with the traditional methodology.

Genetic algorithms are optimization techniques, framed within the evolutionary algorithms, inspired by nature, and collecting a set of models based on the evolution of living beings. They are an optimization techniques, inspired by the Darwinian principle of natural selection and genetic reproduction. In this principle, the fittest individuals have greater longevity and, therefore, greater probability of reproduction (Andaluz, 2004).

METHODOLOGY

The C-Pit problem

The algorithm solves the problem called CPIT +, which is a simplified version of the optimization model presented by Johnson and incorporating geotechnical constraints (Navarro, 2015) (Equations 1 through 5).

The C-Pit maximizes NPV from the life of the mine (Equation 1), using a discount rate (p). The constraint in Equation 2 imposes precedence; if block b′ is the immediate predecessor of block b; then b′ must be extracted in the previous or the same period that the block b is extracted. Constraint in

Equation 3 indicates that each block must be extracted only once. Constraint in Equation 4 ensures that operational capacities are achieved in each period. All variables are binary (Espinoza et. al., 2013)

$$max \sum_{b \in \mathfrak{B}} \sum_{t \in \mathcal{T}} \hat{p}_{bt} x_{bt} \tag{1}$$

$$s.to \sum_{\tau \leq t} x_{b\tau} \leq \sum_{\tau \leq t} x_{b'\tau} \qquad \forall b \in \mathfrak{B}, b' \in \mathfrak{B}_b, t \in \mathcal{T} \tag{2}$$

$$\sum_{t \in \mathcal{T}} x_{bt} \leq 1 \qquad \forall b \in \mathfrak{B} \tag{3}$$

$$\underline{R}_{rt} \leq \sum_{b \in \mathfrak{B}} q_{br} x_{bt} \leq \overline{R}_{rt} \qquad \forall t \in \mathcal{T}, r \in \mathcal{R} \tag{4}$$

$$x_{bt} \in \{0, 1\} \qquad \forall b \in \mathfrak{B}, t \in \mathcal{T} \tag{5}$$

Description of the Genetic Algorithm

The genetic algorithm is a highly parallel mathematical algorithm that transforms a set (population) of individual mathematical objects (typically fixed-length characte strings patterned after chromosome strings), each with an associated fitness value, into anew population (i.e., the next generation) using operations patterned after the Darwinian principle of reproduction and survival of te fittest and after naturally ocurring Genetic operations (notably sexual combination). (Koza, 1992).

To solve the problem of CPIT + using the genetic algorithm, the formulation of four components is required:

- Representation of an individual.
- Genetic operators.
- Phase clustering
- Evaluation of the individual.

Representation of an individual

Within the block model, each block is represented by its spatial coordinates and, for the algorithm, each block is identified through its centroid. Thus, individuals are represented by a subset of centroids. In order to comply with the geotechnical restriction of slope angle and precedence, a truncated cone is used, which is defined by its radial base, its outer angle and the center of the base of the cone (centroid of the block). The truncated cone meets the geotechnical constraints of slope angle through its external angle (δ) and, in addition, its radial base facilitates the operational design and minimum operating widths. A truncated cone represents all the blocks it contains, in Figure 1, a section view of a cone with five blocks of height is observed, and each block represents a bench.

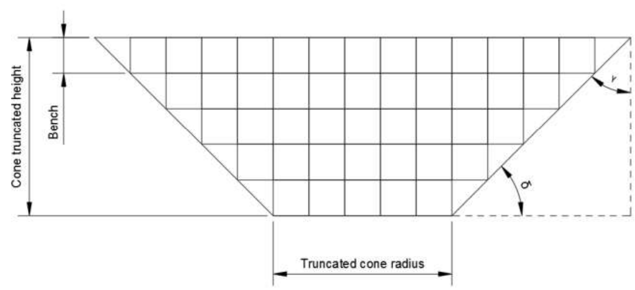

Figure 1 Sectional view of a truncated cone

Genetic operators

The simplest form of genetic algorithms involves three types of operators: Selection, Crossover, and Mutation.

Selection: weighted roulette selection is used, where each individual is assigned a part of the roulette, which is proportional to its fitness.

Crossover: This operator randomly chooses two individual parents, two offspring are generated. Those that correspond, the first of the elements common in both parents and the second of the elements that exist only in one of the parents.

Mutation: the mutation consists of adding or removing a randomly chosen item according to a probability (p = 0.5) (Mitchell, 1999).

Phase Clustering

Before the evaluation of the solution, the problem of truncated cones clustering in phases must be solved. A clustering algorithm, called K-Means is used, which requires a priori the cluster number. Once the grouping is solved, the precedencies are obtained between the blocks of each individual, in addition to excluding the blocks that are already part of an earlier phase. The precedencies of a block are calculated from the truncated cone it represents (Navarro, 2015).

Evaluation of the individual

Once the precedence is defined, the individual is evaluated: the evaluation parameter is the net present value of the extraction of sequence of phases. The scheduling used is of the Phase-Bench-Destination type, where the blocks that share the same characteristic phase-bench-destination are grouped and each group represents an extraction activity that prioritizes the waste. To commence the extraction of the next phase, it is necessary to predetermine a minimum and maximum number of offset benches. When a block is destined to a plant, it adds its tonnage and its processing value; while if a block is not sent to plant, only its extraction cost is added in addition to its tonnage. When mine capacity and processing are reached, there is an increase in the period.

Case study

The block model in study is the model Marvin 30 (Figure 2), available in the library Minelib. The valuation used is as detailed in the datasets of the library (Table 1) (Espinoza et. al., 2013).

Table 1 Characteristics of the Marvin 30 Block Model

N° blocks	**53271**
Element of interest	Cu
Block size	30 m * 30 m * 30 m

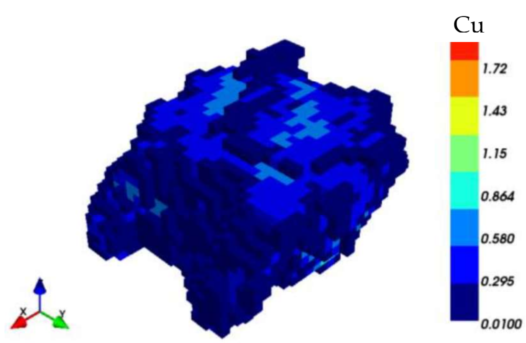

Figure 2 Isometric view of the Marvin 30 block model

Traditional Methodology

A set of nested pit was generated with revenue factor from 0 to 1, with steps of 0.1; they were submitted to schedules of type best and worst case, where the best case is a pit by pit extraction while the worst case is bench by bench extraction. The total capacity restriction was equal to 60 million tonnes.

In addition, a phase-bench-destination type schedule was performed, with three phases resulting from the clustering of nested pit; this type of scheduling was described in the subsection Evaluation of the Individual. The scheduling was executed with two capacity constraints: mine constraint equal to 60 million tons and plant constraint equal to 20 million tons. For the clustering of the nested pit in phases was used as criterion the phase respect the minimum operating widths. A constant slope angle of 45 ° was used.

Genetic Algorithm Methodology

For scheduling, the same mine and plant capacity constraints were used as for traditional methodology. Additional parameters entered in the genetic algorithm were population size and number of generations. The slope angle was taken as constant and equal to 45 ° while the cone radius was two blocks. In order to choose the number of blocks that would be equal to the radius of cone in its radial base, the minimum load width of a payloader and a truck, equipment necessary for the extraction of material at the bottom of a phase, were calculated using Equation 6. The minimum load width (MLW) is equal to 40 m and, if each block is equal to 30 m, the radius of the minimum cone would be equal to two blocks, which would correspond to the width of the radial bases of the phase.

$$MLW = B + 3Ds + \frac{Lt}{\sqrt{2}} + Wp \tag{6}$$

In order to determine the optimum cluster number, the block model was divided into groups of 1 to 10. The NPV generated by each group of phases and then the operating width of the load in each phase were analyzed. It was found that the highest NPV was reached when the model was divided into 8, however, when analyzing the operative widths the set was found infeasible. Another number of cluster that generates good results of NPV is three and its operative widths respect the minimum. Subsequent tests were performed with this cluster number. Tests were started by increasing population size and number of generations. As both parameters increased, the NPV result improved. Table 2 shows the results of the different schedules and their NPV values.

Table 2 Results of the different schedules.

Scheduling type	Period (Years)	NPV (MUS$)	Relationship with BC (%)
Best Case	9	1,003.59	
Worst Case	17	510.68	-49
Nested Pit FBD	17	681.05	-32
Genetic Algorithms	15	592.15	-40

RESULTS AND DISCUSSION

NPVs, phase size and production schedules were compared for the two types of methodologies applied. Table 2 shows the results for the different types of scheduling and their relation to the best case value. The results of the genetic algorithm are compared with the scheduling nested pit phase-bench-destination. In both cases, we have 3 phases; the genetic algorithm's NPV is 15% lower that nested pit FBD's NPV. If we analyse the minimum load width, the nested pit FBD's of phase two do not comply with this parameter; while genetic algorithm's phases comply with the minimum. The width operational of the phases are observed in Figure 3. Finally, when we compare genetic algorithm's NPV with worst case's NPV, the genetic algorithm's NPV is 15% higher than worst case's NPV. Figure 4 shows the production plans for both methodologies. The genetic algorithm's scheduling satisfies, in all the periods, the constraint of capacity plant. In addition, the grade is more stable as compare with the traditional methodology.

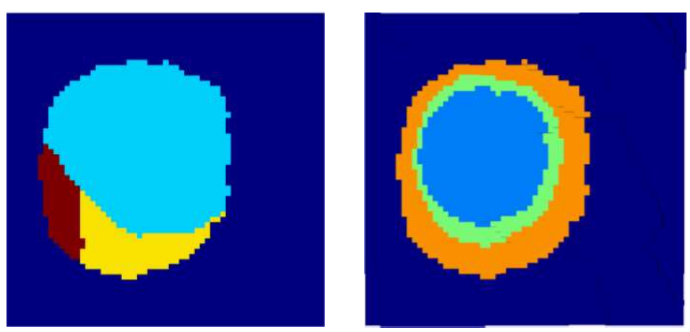

Figure 3 Phase Set: Genetic Algorithm (left) and Nested Pit FBD (Right)

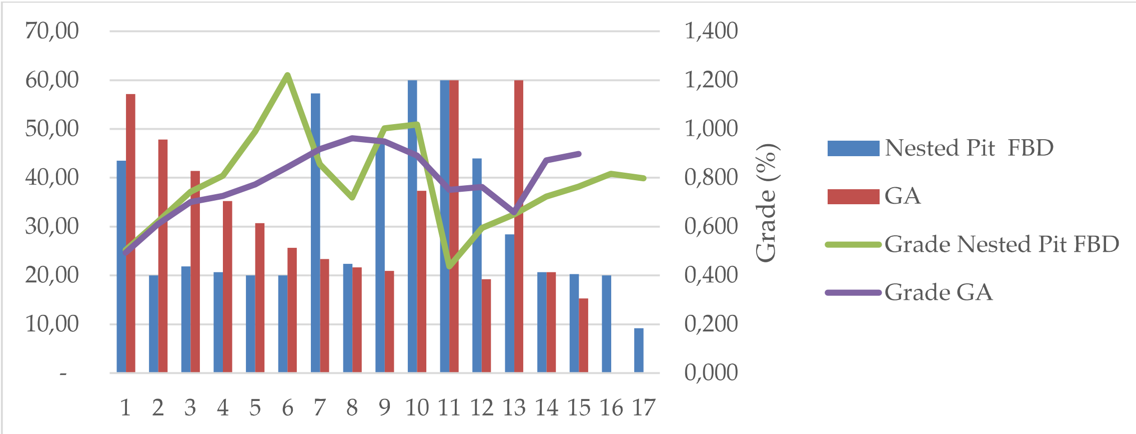

Figure 4 Production scheduling: nested Pit FBD and genetic algorithm

CONCLUSION

Through the genetic algorithms, volumes (phases) were generated that fulfilled the operational and geotechnical restrictions, such as, the minimum width of operation and slope angle. It was demonstrated that the use of the truncated cone could replace the use of more complex structures. The scheduling of the phases generated a feasible production scheduling with values of NPV 15% higher than that reached by the traditional scheduling type worst case scenario. The generation of high values of NPV depends largely on the population size and number of generations based on which the genetic one is executed; the choice of these parameters has a high correlation with the available computational capacity.

ACKNOWLEDGEMENTS

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NOMENCLATURE

FBD	Phase-bench-destination
MLW	minimum load width
B	Safety berm
Ds	Safety distance
Lt	Long truck
Wp	Width payloder
δ	Outside angle of the truncated cone

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