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An Extended Stochastic Optimization Method for Multi-Process Mining Complexes

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Abstract: Traditionally, mining engineers plan an open pit mine considering pre-stablished conditions of operation of the plant(s) derived from a previous plant optimization. By contrast, mineral processing engineers optimize the processes of a plant through considering a regular feed from the mine, with respect to quantity and quality of the materials. The methods implemented to optimize mine and metallurgical plans simultaneously are known as global or simultaneous optimizers. The development of these methods has been of major concern for the mining industry in the last few years. Some algorithms are available in commercial mining software packages however, these algorithms ignore the inherent geological uncertainty associated with the deposit being considered, which leads to shortfalls in production, quality, and cashflow expectations.

This paper presents a heuristic method to generate life-of-mine production schedules that consider the whole single-pit mining complex and account for geological uncertainty, which allows for controlling the risk associated with not meeting production and blending requirements while maximizing the net present value expectations. The method uses iterative improvement by swapping periods and destinations of the mining blocks to generate the final solution. It considers multiple processes that may have several processing options with their corresponding costs, recoveries, additives and blending requirements associated. For meeting the blending requirements, multiple metallurgical ore types, attributes and properties related to each mining block can be considered. The stockpiling of the different metallurgical ore types is also incorporated in the method. Its implementation at a copper deposit shows its ability to control mine and processing capacities while increasing the expected net present value of an initial solution by 30%.

Key Words: Stochastic global optimization, geological uncertainty, mine production schedule.

1 Introduction

The quality of the input material of a metallurgical process may determine its corresponding throughputs, costs and recoveries. Mill throughput can be sensitive to rock hardness, work index or the ratio of clay materials; costs and reaction times in an autoclave depend on sulphur content; recoveries are affected by deleterious materials (Wharton 2004). There are several methods available in mining and metallurgical software packages to optimize the different parts of a mining complex in isolation. The process of optimizing all parts of a mining complex simultaneously is known in the mining literature as global optimization (Whittle, 2010). This is a problem with high complexity due to the link between time periods and discounting, the blending requirements, the flexibility generated from the stockpiles, the multiple processing alternatives, and the variability and uncertainty associated with grades and physical characteristics (Whittle 2007).

Over the last decade, several algorithms that seek for generating optimal solutions have been developed. Hoerger, Seymour and Hoffman (1999) formulate the problem of optimizing the simultaneous mining of multiple sources (pits and underground mines) and the delivery of ores to multiple plants as a mixed integer program. The model calculates the net present value of the mining complex by using variables that represent material sent from the mines to the stockpiles, material sent from the mines to the processes, and material sent from the stockpiles to the processes and their corresponding associated costs. The blocks are grouped into increments based on the metallurgical properties, which belong to sequences (or pushbacks). The integer variables are used to model mine sequencing constraints at a pushback level and plant startups and shutdowns. Due to the use of pushback sequencing constraints instead of block sequencing constraints to decrease the complexity of the problem, there is a loss of resolution in the solution generated from the method that may lead to the inability of meeting the blending and production requirements. Furthermore, the method does not consider multiple processing options for each process and ignores the geological uncertainty associated with the ore deposits. Whittle (2007) presents the Prober optimizer for global optimization that aggregates the mining blocks into parcels of mine material type. These material types are defined from different grade bin categories; that is, for each relevant grade or attribute, cut-offs are defined to allow flexibility for blending purposes. The method considers stockpiles for each material type that may be combined with the material obtained directly from the mines to satisfy the different process requirements. Prober uses a random sampling and a local optimization approach to generate the solution. The random sampling consists of a search algorithm that samples the feasible domain of alternative LOM (life-of-mine) mining plans; the local optimization is an evaluation routine that determines the optimal cut-off grade, stockpiling, processing selection, blending and production plan and determines the NPV (net present value). The optimizer works by repeatedly creating a random feasible solution and then finding the nearest local maximum. The various NPVs that the algorithm finds are stored, and the run is usually stopped when the top ten values lie within 0.1 per cent of each other. Although very flexible and able to handle complex blending operations, the algorithm has some drawbacks: it groups the parcels into panels and assumes that the parcels are consumed in the same proportion within a panel; good solutions may be found but it does not guarantee optimality; and, geological uncertainty is discarded.

Regarding geological uncertainty, some approaches have been developed in the last decade to account for grade and material type uncertainties into pit design and mine production scheduling. Ramazan and Dimitrakopoulos (2004) formulate the mine scheduling problem as a two-stage stochastic integer program (SIP) in which the first stage variables represent mining decision variables and the second stage variables represent deviation from grade and production targets evaluated on a set of orebody simulations. The formulation was later extended to include stochastically designed stockpiles and multiple processors. Leite and Dimitrakopoulos (2008) implement the method in a copper deposit generating net present value expectations more than 20% greater than the ones obtained using conventional deterministic methods. Bendorf and Dimitrakopoulos (2009) expand the stochastic integer programming approach to multi-element deposits and include equipment size and mineability constraints to facilitate accessibility. Jewbali and Dimitrakopoulos (2009) incorporate short-scale deposit information and related grade uncertainty into the SIP formulation, thus allowing for realistic integration of short- and long-term mine production schedules, to obtain more reliable mine production forecasts. Although, the SIP formulation generates substantial improvements in terms of net present value expectations and meeting production targets, industry standard optimizers such as CPLEX are unable to solve big size problems due to the large amount of integer variables, thus alternative solution avenues are being sought (Lamghari and Dimitrakopoulos, 2012).

Many different approaches are available to solve large combinatorial optimization problems. Some of them have been implemented for solving complex mine scheduling optimization problems. Godoy (2003) and Godoy and Dimitrakopoulos (2004) develop a multi-stage method for mine production scheduling that integrates the joint local geological uncertainty and uses simulated annealing (SA) algorithm. The method seeks to generate a risk-based mine production schedule that minimizes deviation from ore and waste production targets. Leite and Dimitrakopoulos (2007) apply the method at a copper deposit obtaining net present value expectations more than 20% greater than the ones obtained using conventional deterministic schedulers. Albor and Dimitrakopoulos (2009) implement the method at the same copper deposit and observe that the schedule obtained was not particularly sensitive after 10 orebody simulations. Furthermore, the authors point out that the stochastic final pit limit was 17% greater than the deterministic one, adding 9% to the net present value expectations. Montiel and Dimitrakopoulos (2011) extend the formulation to mining complexes with multiple ore material types and multiple processing streams and implement it at a large disseminated copper deposit obtaining substantial reductions in the expected deviations from the different processing targets. Goodfellow and Dimitrakopoulos (2011) develop a simulated annealing implementation for pushback design to control deviation from pushback size targets considering different material types and processing plants. Lamghari and Dimitrakopoulos (2012) implement tabu serach (TS) and variable neighbourhood search (VNS) for the mine scheduling problem obtaining near-optimal solutions while outperforming CPLEX in terms of computational time. Lamghari et Al. (2012) develop a hybrid approach that combines exact methods and metaheuristics for solving the LOM production scheduling problem.

This paper presents a methodology for generating mine production and blending schedules in mine complexes that contain multiple elements, metallurgical ore types, stockpiles, processing streams, and blending requirements and considers geological uncertainty; that is, uncertainty in grades and material types. The following section describes the main features of the method and its different stages. Later, the results obtained from the implementation of the method at a copper deposit are displayed, and finally some conclusions and future research avenues are addressed.

2 An Extended Stochastic Optimization Method

2.1 Generalities

The method described in this paper seeks to generate a LOM production schedule that maximizes the expected net present value of a mining complex through the optimization of the different stages: mining, blending, processing. The method considers single pit mining complexes where multiple elements, ore types, stockpiles, and processing options may be available. It also considers geological uncertainty by using grade and material type orebody simulations. For each ore type, there is a corresponding stockpile with infinite capacity associated. At each process, several processing options may be available; a processing option has its particular costs, recoveries and blending requirements. An example of a process with two processing options can be a mill in where the option 1 is to mill with low silica content which increases the productivity of the mill and reduces operating costs while option 2 is to operate with high silica content with its corresponding outputs. Based on the capacities and blending requirements, the method determines the destination of the material and the processing option implemented. The method also considers additives for each process; that is, a given process may have several additives that control its rate of production. The required amount of these additives depends on the quality of the input material; i.e., the grade of the different attributes. In a milling operation, it is well known that the rate of production depends on geo-metallurgical properties such as hardness, work index, silica content, etc. It is possible to define, based on the different attributes, the time required to mill a certain block. Expressing the processing time as a function of the different attributes and the tonnage of the blocks, and knowing the availability in hours of the mill per year, it is possible to determine more accurately the expected rate of production of that particular mill. This rate of production can be seen as a function of the grade of the different attributes and not only the tonnage of the material.

The time required to process the material may, therefore, be considered as an additive of the mill process with some available hours per year. A different example is that of additives in an autoclave process, etc.

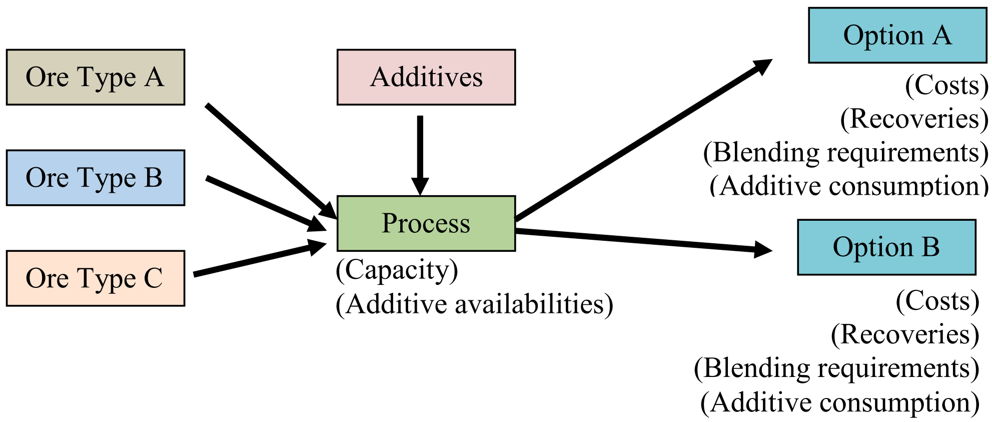

Figure 1: Process and processing options.

The costs and recoveries are defined for each processing option and for each ore type. The blending requirements are modelled as upper and lower limits for the different attributes. The recoveries and the additive consumption can be considered constants for each material type, or, can be expressed as functions of the different attributes.

2.2 The objective function and constraints

The objective function of the proposed method is given by the sum of the discounted revenues obtained by selling the different recovered metals (or attributes) minus the discounted costs associated to the different parts of the operation throughout the different periods and simulations:

$$MaximizeO = \sum_{s=1}^{S}\sum_{p=1}^{P}\left(\frac{(revenue(s,p) - MineCost(s,p) - process(s,p) - StockCost(s,p) - rehandle(s,p))}{(1+d)^p}\right) \quad (1)$$

where *revenue(s,p)* represents the income obtained by selling the different recovered metals of the mining complex in simulation s and period p; *MineCost(s,p)* is the cost of mining the material in simulation s and period p; *process(s,p)* is the cost of processing the material sent to the different destinations in simulation s and period p; *StockCost(s,p)* is the cost of sending the material from the mine to the stockpiles in simulation s and period p; *rehandle* is the cost of sending material from the stockpiles to the different destinations in simulation s and period p; S is the set of orebody simulations; P is the number of years of production; and d is the discount rate. The value of the objective function O is the sum of the net present values of the different simulations.

$$revenue(s,p) = \sum_{r=1}^{R}\sum_{v=1}^{V}\left(\sum_{B}(MB_v * Rc * (MP_v - SL_v)) + \sum_{SP}(MS_v * Rc * (MP_v - SL_v))\right). \quad (2)$$

For the simulation s in the period p, the revenue is given by Equation (2). R represents the set of destinations (processing options); V is the set of recovered metals (or attributes); B is the set of blocks mined in period p; SP is the set of stockpiles; MSv is the amount of attribute v sent from a particular stockpile to a given destination in the simulation s in period p; MBv is the amount of variable v presented in a particular block in the simulation s; Rc is the metallurgical recovery that depends on the metallurgical ore type of the block (or stockpile) and the destination; *MPv* is the price of the recovered attribute v, and *SLv* its selling cost.

$$process(s,p) = \sum_{r=1}^{R} \left(\sum_{B} (TB * Pc) + \sum_{SP} (TP * Pc) \right). \tag{3}$$

The *process* cost for each year and simulation is calculated using Equation (3). *TB* represents the tonnage of a given block in simulation s; *TP* is the tonnage sent from a given stockpile to a particular destination r in simulation s in period p; and *Pc* is the processing cost that depends on the metallurgical ore type and the destination.

Similarly, and accounting for the tonnage of the blocks and stockpiles and the per-unit costs, the *MineCost*, *StockCost* and *rehandle* are calculated for each year and simulation.

The amount of material sent to a given process (no matter which processing options are used) is given by Equation (4). Equation (5) represents the average grade of a particular attribute of the material sent to a given destination (processing option). The consumption of a given additive of a particular process is expressed in Equation (6).

$$tonnage\_process(s,p) = \sum_{PO} \left(\sum_{B} TB + \sum_{SP} TS \right), \tag{4}$$

where *PO* are the processing options available for that particular process; *B* is the set of blocks sent to a particular destination (processing option); *SP* is the set of stockpiles; *TB* is the tonnage of a particular block sent to a given destination; and *TS* is the tonnage sent from a given stockpile to a particular destination.

$$average\_grade(s,p,r,v) = \frac{\sum_{B} MB_v + \sum_{SP} MS_v}{\sum_{B} TB + \sum_{SP} TS}, \tag{5}$$

where *MSv* is the amount of metal v sent from a particular stockpile to destination r in the simulation s during the period p; *MBv* is the amount of metal v presented in a particular block sent to destination r during period p in the simulation s; *TB* and *TS* are tonnages defined as before.

$$additive\_consumption(s,p,r,a) = \sum_{B} TB * Ac + \sum_{SP} TS * Ac \tag{6}$$

where *Ac* is the additive consumption coefficient of additive a in destination r that depends on the metallurgical ore type of the input material.

The constraints of the method are:

Block precedence constraints: The slope constraints regarding the different geotechnical zones cannot be violated (hard constraints).

Capacity constraints: For the mine and the different available processes. For a given process, it accounts for the total tonnage mined at that process, no matter which processing option is used (Equation (7)). The constraint states that the tonnage sent to a given process in a given period p in a particular simulation s must be less or equal to the capacity of that process in that period. $tonnage\_process(s,p)$ is defined as in Equation (4).

$$tonnage\_process(s,p) \le capacity\_process(p) \tag{7}$$

Blending constraints: For the different destinations (processing options). For each attribute, there can be upper and lower limits. The average grade of a given attribute v in a given destination r must be greater than the lower limit and smaller than the upper limit. $average\_grade(s,p,r,v)$ is defined as in Equation (5).

$$Lower\_Limit(v,r) \le average\_grade(s,p,r,v) \le Upper\_Limit(v,r) \tag{8}$$

Availability constraints: For the additives associated to the different processes. The rate of consumption of the additives can depend on the grades of the different attributes of the material. The amount of additive a related to destination r consumed in period p in simulation s must be less than or equal to the availability of that additive in that period. $additive_consumption(s, p, r, a)$is defined as in Equation (6).

$$additive\_consumption(s, p, r, a) \leq availability(p, a) \quad (9)$$

An initial solution is perturbed to maximize the objective function while considering the set of constraints. Capacity, blending and availability constraints can be relaxed based on a user-defined probability level; that is, given a 90% probability level, these constraints can be violated in at most 10% of the simulations at each iteration. This relaxation permits to explore more profitable solutions by maintaining the level of risk under pre-specified tolerable limits. For the rest of the paper this set of constraints with their relaxation are named target constraints.

2.3 Stages of the method

The method proposed in this paper uses iterative improvement over an initial solution to generate the final solution. The procedure that the method uses can be divided in three stages: (i) Assign periods and destinations to the blocks based on the initial solution; (ii) Calculate the overall profitability per block per destination based on the orebody simulations; and, (iii) perturb the initial solution until a stopping criteria is reached to generate the final solution.

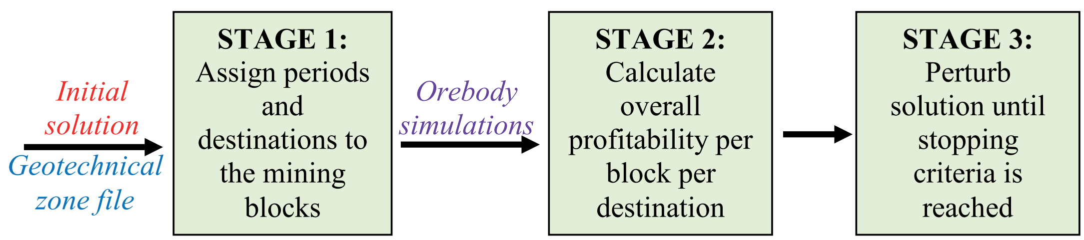

Figure 2: Stages of the method.

2.3.1 Stage 1

In this stage, the method assigns periods and destinations to the mining blocks from the initial solution. It also assigns a geotechnical zone for each block based on the geotechnical zone file. Different zones can have different slope angles, so that, the zone at which a given block belongs to, determines its set of predecessor and successors blocks. If there are some slope constraint violations in the initial solution, block mining period corrections are performed based on the different slope angles. For doing so, when a slope constraint violation is found, the mining period of the block is moved to an available period based on the set of successor and predecessor blocks; that is, the range between the latest period of the predecessor blocks and the earliest period of the successor blocks (Figure 3).

2.3.2 Stage 2

At this stage, the orebody simulation files are read, and the profits and costs for each simulation and period are evaluated. From the material types and grades at each simulation, the proposed method calculates, for each block, the overall profitability per available destination; that is, it evaluates the profit (or loss) obtained by sending a particular block to a given destination and accumulates it through the set of simulations (Figure 4). From there, the method evaluates the optimal destination for a particular block, but, this optimal destination may not be the final destination due to capacity, availability and blending constraints (target constraints).

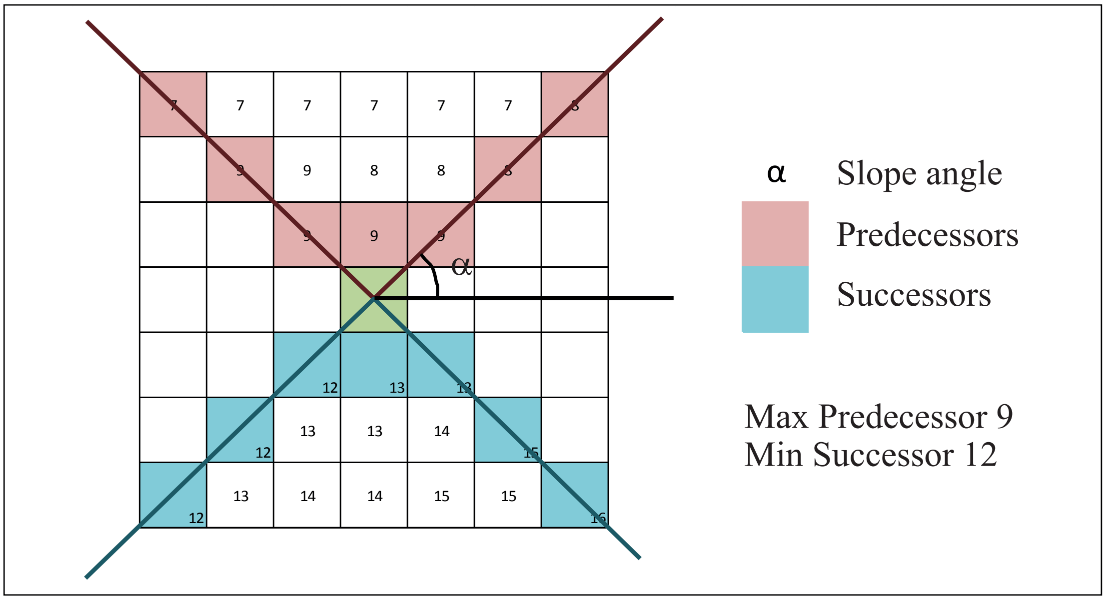

Figure 3: 2D example of predecessors and successors of a given block.

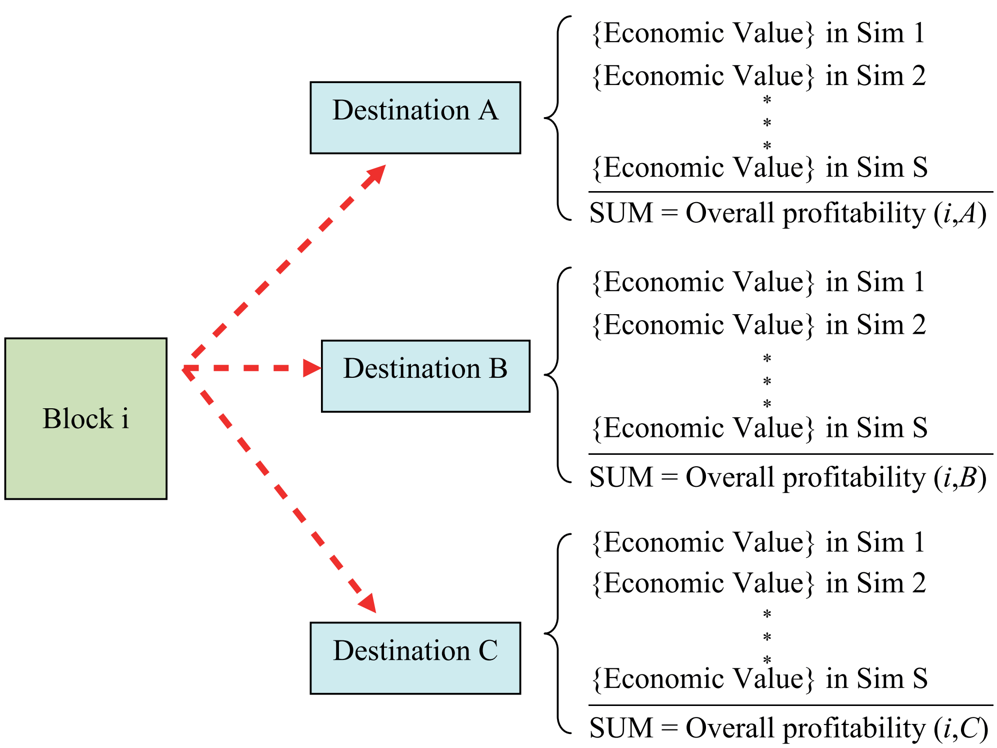

Figure 4: Overall profitability per block per destination.

2.3.3 Stage 3

This is the perturbation stage. A block is selected randomly and the available destinations for that particular block are sorted based on its overall profitability. If the best destination has a positive overall profitability, i.e., it increases the value of the objective function, the block is pushed to early periods, otherwise it is pushed to later periods.

For positive overall profitable blocks, the method defines four possible options for periods and destinations (Figure 5). The *first option* is to send to block to its best destination in the previous period (current period – 1). If there are no slope and target constraint violations this option is chosen. The *second option* is to find an early available period and a profitable destination where the block can go without violating slope and target constraints; that is, the periods between the current period and the latest period of the set of predecessor blocks, and the destinations with positive overall profit. The *third option* is to find an adjacent block from which a double swapping that increase the objective function can be performed without violating slope and target constraints. The double swapping consists of two adjacent blocks switching mining periods. If no double swapping is available, the block is sent to the stockpile, which is the *last option*.

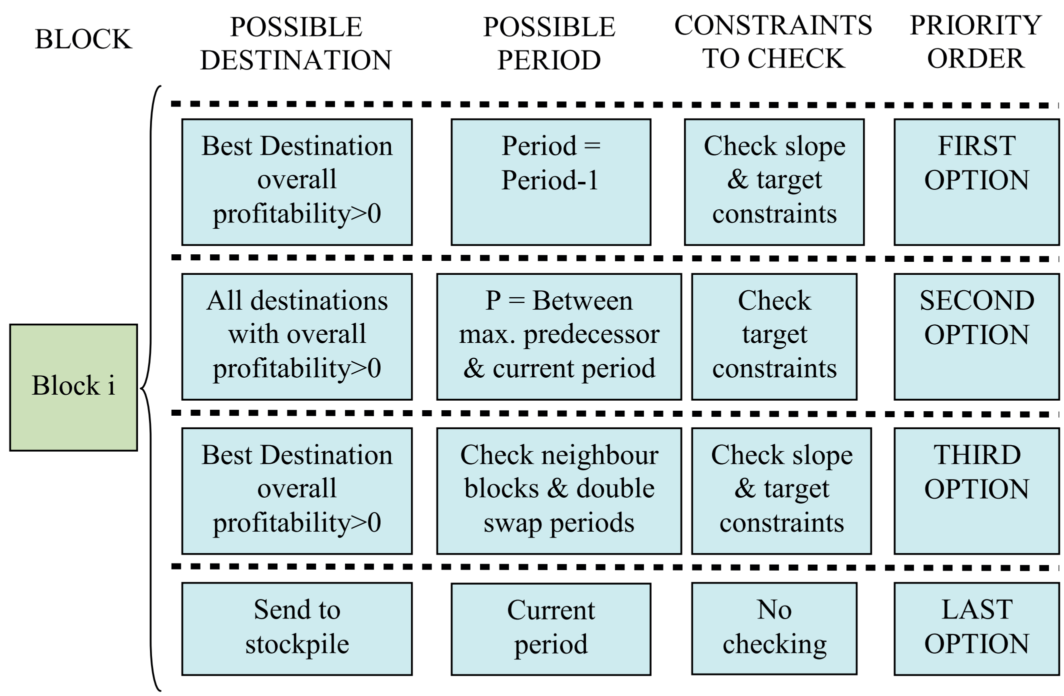

Figure 5: Possible destinations and mining periods of a block with positive overall profitability.

If the block has a negative overall profit for all the different destinations, it is sent to the waste dump. To decide the period when the block is going to be mined, the method evaluates the overall profitability of the set of closest successor blocks. If the sum of the overall profitability of the closest successor blocks is positive, the period of the block does not change to allow the successor blocks to move to early periods. This permits the schedule to access profitable areas early even when waste blocks are overlying them. If the sum is negative, the block is mined in a later possible period without violating slope and mine capacity constraints. It assigns a period between the subsequent period (current period + 1) and the earliest period of the set of successor blocks.

It should be noted that the method uses an overall revenue cut-off instead of a grade cut-off that conventional methods use to discriminate between ore and waste. The material sent to stockpiles is a profitable material that cannot be processed immediately due to capacity, availability and blending constraints.

Every user-defined amount of iterations, the method calculates or updates the overall profitability of the stockpiles regarding the different destinations and sends the material from the stockpiles to the most overall profitable destinations along the different periods without violating target constraints.

The method stops after a pre-defined number of iterations, period swaps, or iterations without substantial improvement of the objective value, are reached. The maximization of the objective value is driven by sending the most profitable blocks to early possible periods and the best available destinations and sending to the waste dump the blocks with negative overall profit in later possible periods without violating slope and target constraints. The constraints are respected by means of the checking mechanism throughout the iterations of Stage 3. The Figure 6 shows the flowchart of the method in the stage 3.

The method generates a mine production schedule that determines the periods and destinations of the different mining blocks. Additionally, it determines the material that is re-handled from the stockpiles at each simulation, given that the quantity and quality of the material sent to the stockpiles varies with simulations.

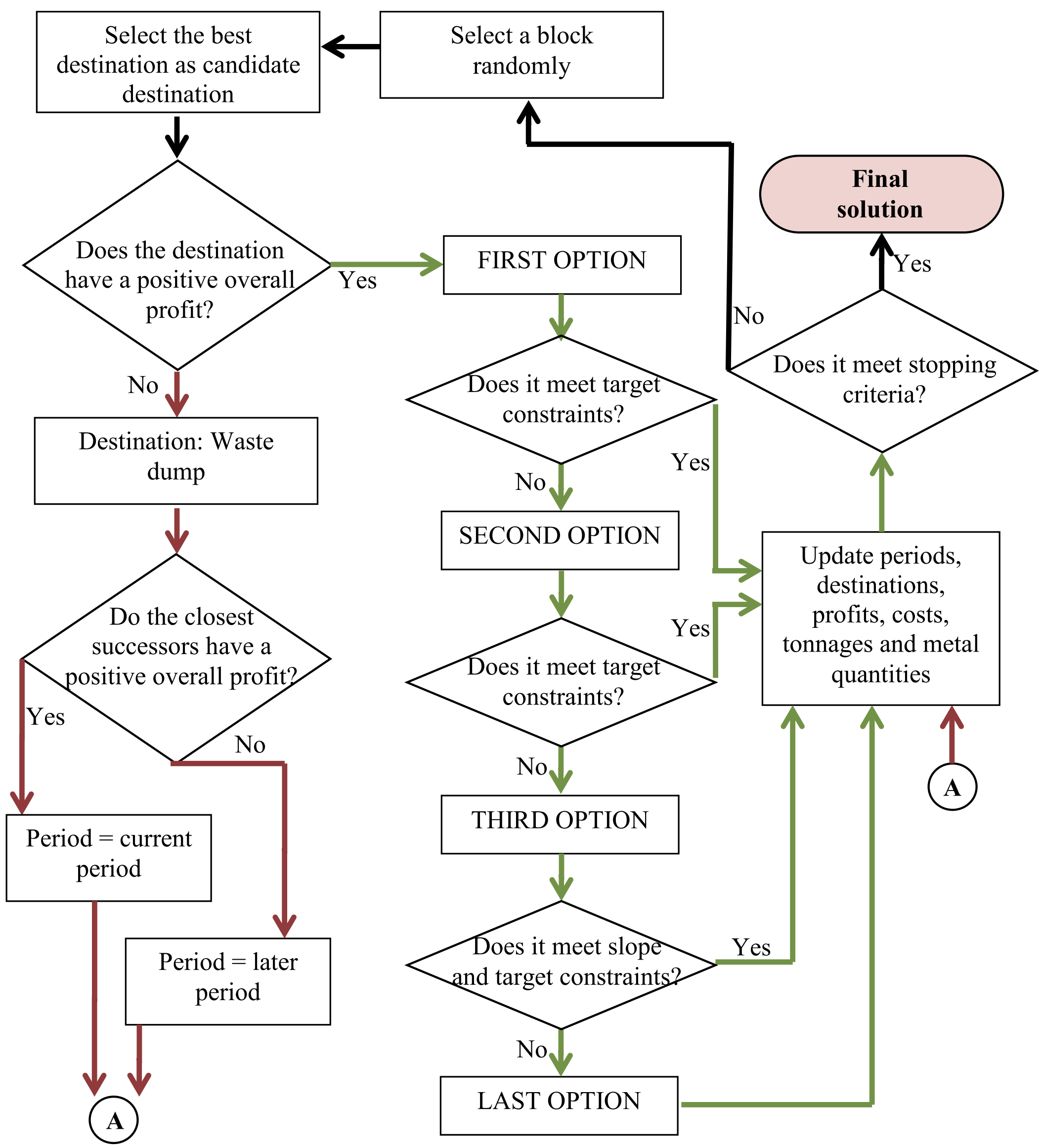

Figure 6: Stage 3 of the proposed method.

3 Case Study: A Copper Deposit

The method was implemented at a copper deposit, from which 50 orebody simulations are available for modelling geological uncertainty. Figure 7 shows the different material types and the available processing destinations in the mining complex.

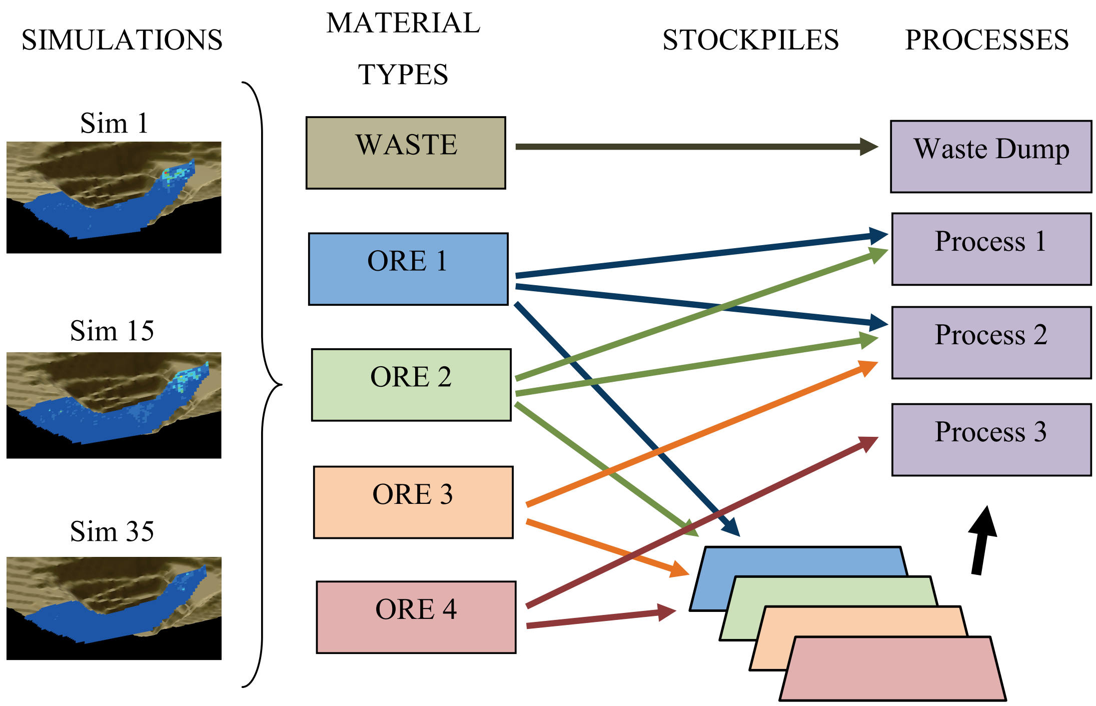

Figure 7: Available material types and destinations.

Several mining sequences were generated using a conventional optimizer. Figure 8 shows different possible initial solutions generated from different orebody simulations.

The proposed method seeks to generate a mine and destination schedule that maximizes the NPV and respect, within a user-defined probability level, the capacity, availability and blending constraints. For doing so, an initial solution is iteratively perturbed for improving the objective value. To identify the number of perturbations required in perturbation stage, different amount of perturbations were tested and the deviations from target constrains evaluated. Figures 9 and 10 shows the evolution of the percentile 50 (P50) of the tonnage sent to process 1 and the total tonnage mined with the number of perturbations. It is observed a large deviation from capacities at small number of perturbations and a substantial reduction in the deviation driven by the increment of the number of perturbations; i.e., the reduction in deviation from capacity of process 1 decreases from 9% in average to 0.2% when increasing the number of perturbations from 100 thousand to 1 million. Regarding the total mine production, the average deviation in the first 16 years remains in the same level (around 4% from the mine capacity).

An analysis based on the value of the expected NPV was performed. Figure 11 shows the evolution of the expected NPV with the number of perturbations.

It is observed that the increment of the expected NPV is marginal after 1 million perturbations. There is no substantial benefit in increasing the number of perturbations there-after. The objective value is increased by 30% when compared to the initial solution. The same analysis was done regarding the number of simulations required. Figure 12 shows the evolution of the expected NPV with the number of simulations. It can be observed that after 15 simulations, no significant improvement in the expected NPV is presented. Although this analysis just considers the expected NPV, the simulations play an important role in controlling deviation

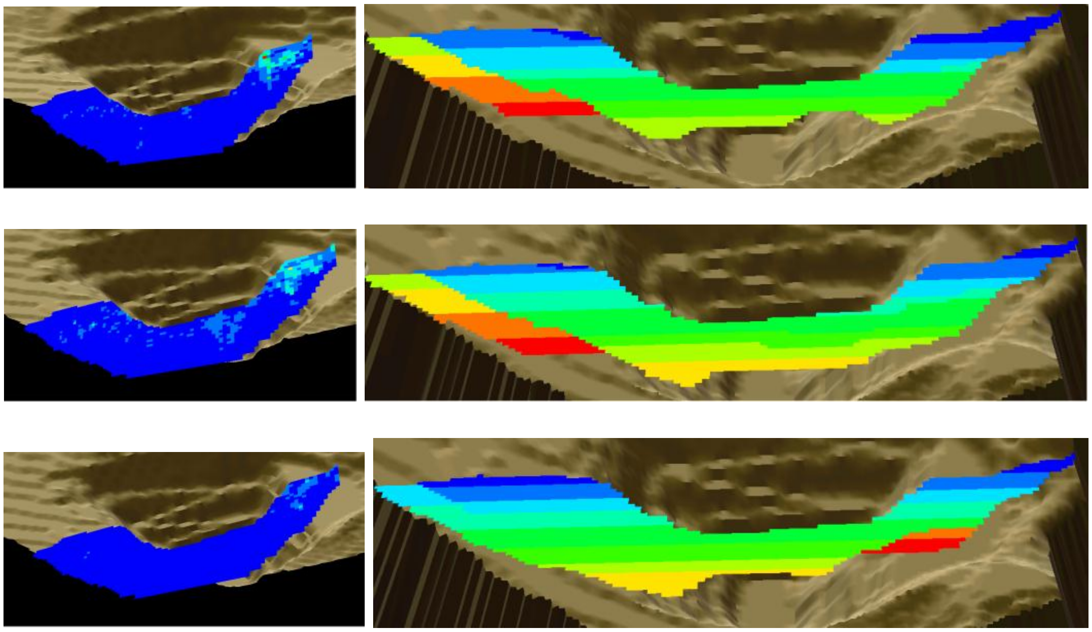

Figure 8: Orebody simulations (left), mining sequences (right).

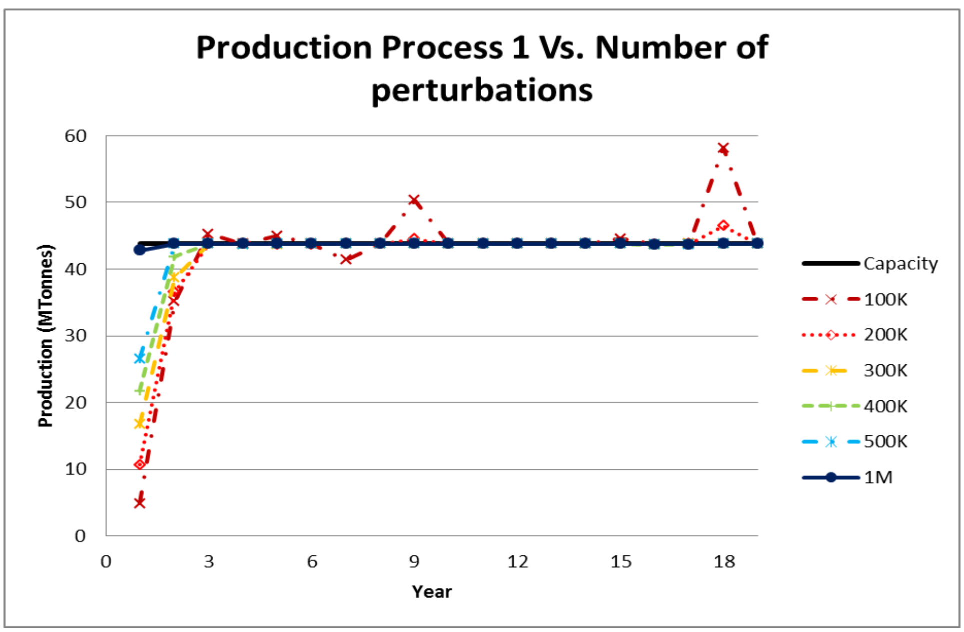

Figure 9: Process 1 production Vs. Number of perturbations for pre-adjustment.

from target constraints, so that the required number of simulations may be larger when considering complex blending operations.

Figures 13, 14, 15 and 16 show the tonnage sent to Process 1, 2, 3 and the total tonnage mined respectively. Given that the solution states the destination of the blocks, the differences in tonnage of the material sent to a given destination through the different simulations are negligible. These minor differences are generated from different tonnages of blocks among simulations derived from simulated densities. If the tonnage of the

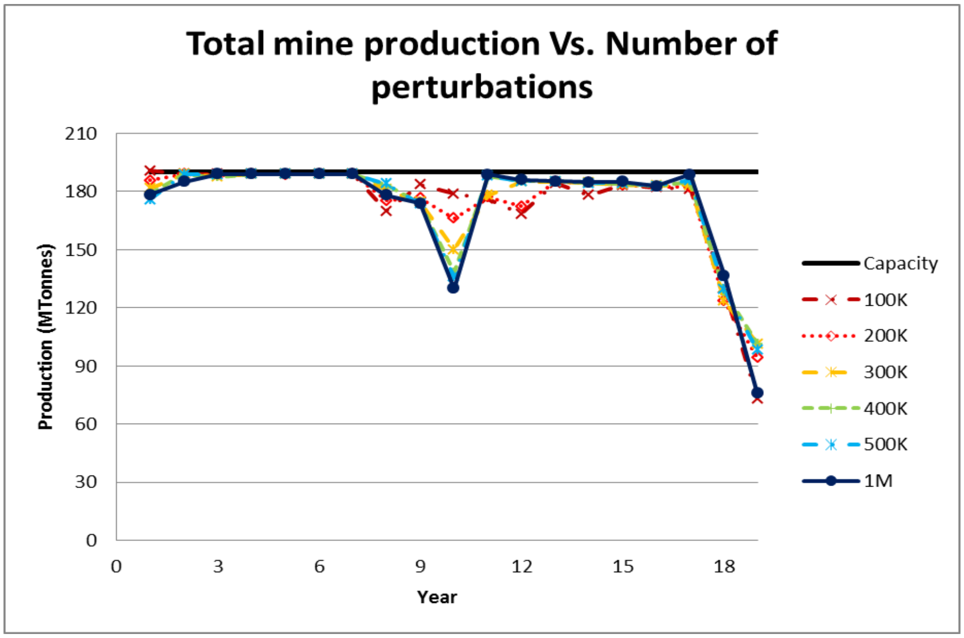

Figure 10: Total mine production Vs. Number of perturbations for pre-adjustment.

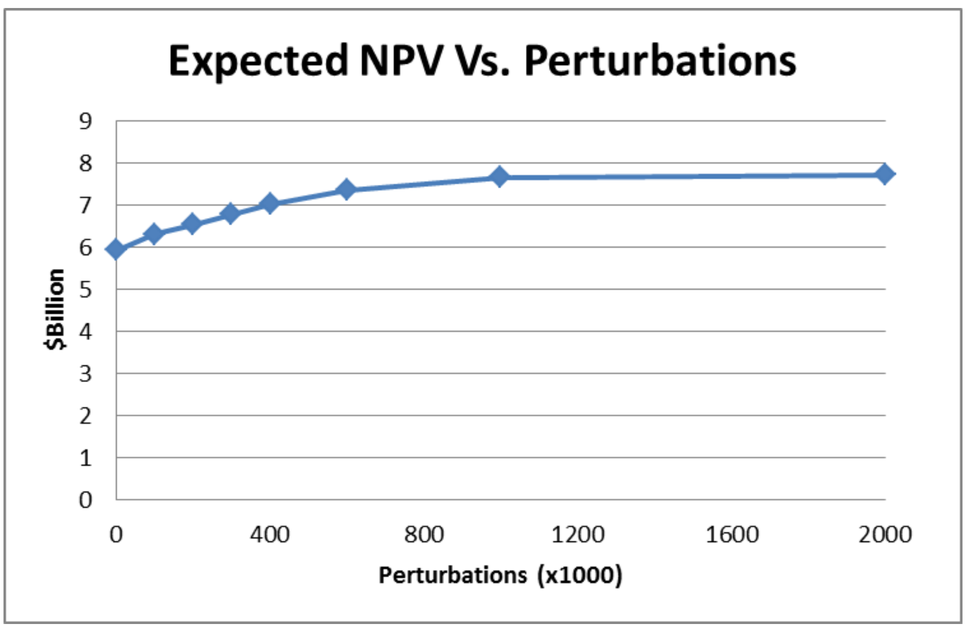

Figure 11: Expected NPV Vs. Number of perturbations.

blocks were similar along the different simulations, no differences were presented in terms of tonnage among simulations. It can be observed that the Process 1 and the total tonnage mined are controlled by their corresponding capacities, whereas the Processes 2 and 3 are controlled by the amount of profitable reserves for those destinations.

Although the material sent to the different destinations does not vary significantly between simulations, the amount of metal recovered has significant fluctuations (Figure 17). This originates from the grade and material type uncertainties; that is, the amount of metal sent to a process change in the simulations due

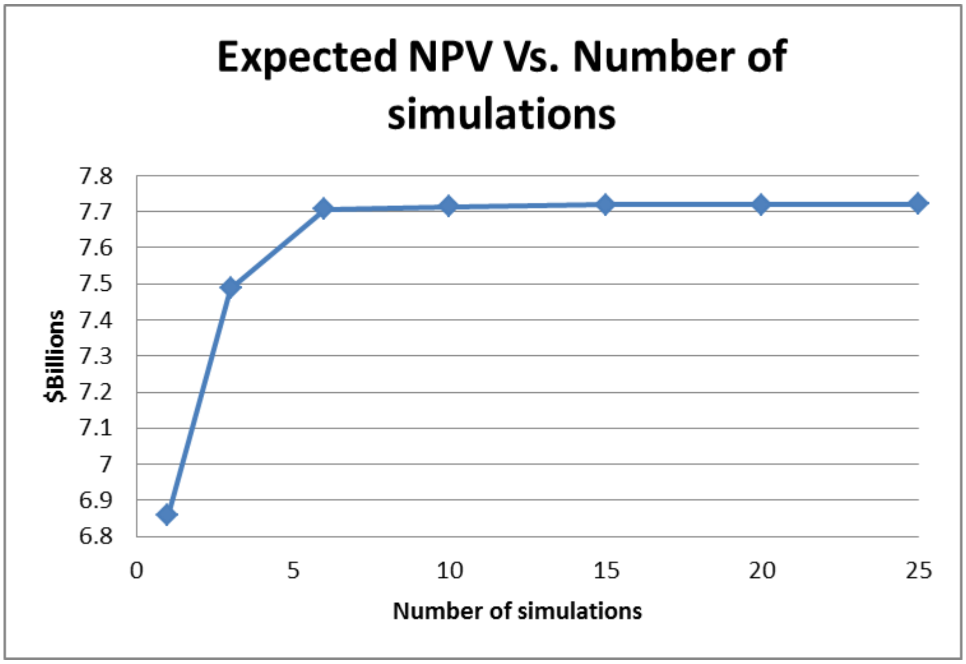

Figure 12: Expected NPV Vs. Number of simulations.

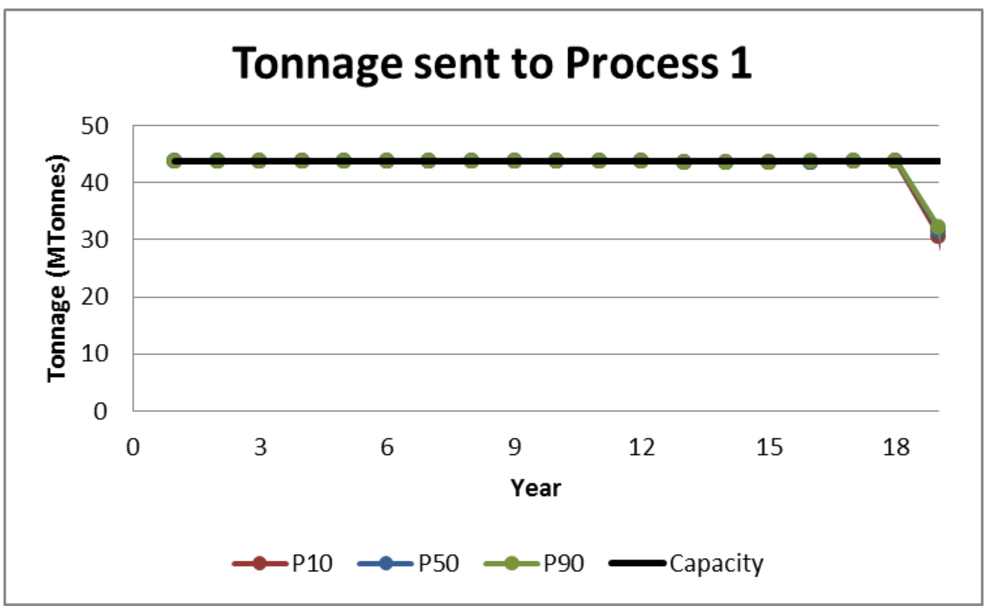

Figure 13: Tonnage input to Process 1.

to grade uncertainty, and the metallurgical recovery at a given destination vary in the simulations due to material type uncertainty.

Figure 18 shows the amount of the different material types sent to the stockpiles. Sending waste material to the stockpile may be seen as a misclassification error. Although there are some risks of misclassifying material by following the stochastic solution generated, the algorithm seeks for minimizing the misclassification errors; that is, sending waste material to the stockpiles or sending a given material type to a non-profitable

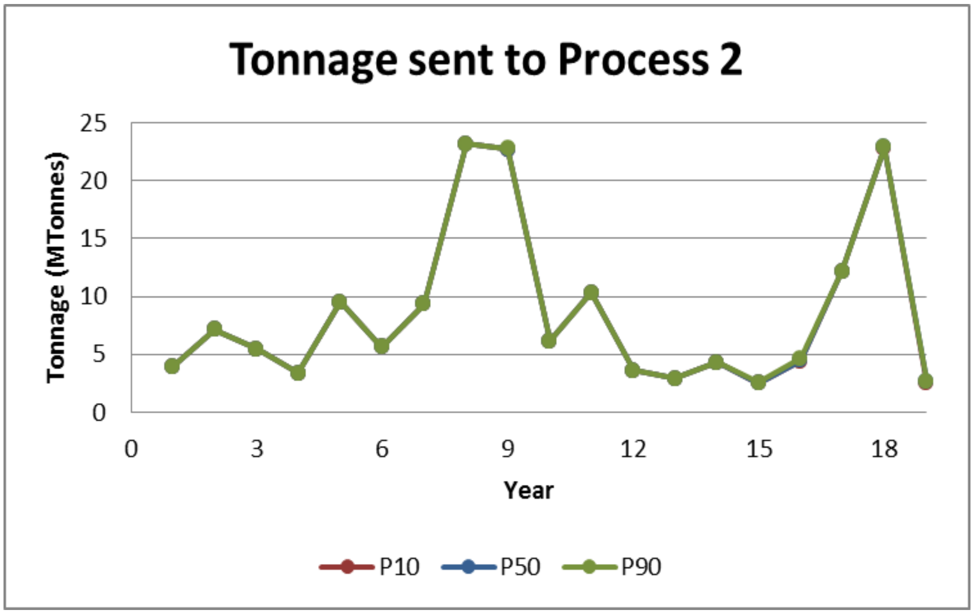

Figure 14: Tonnage input to Process 2.

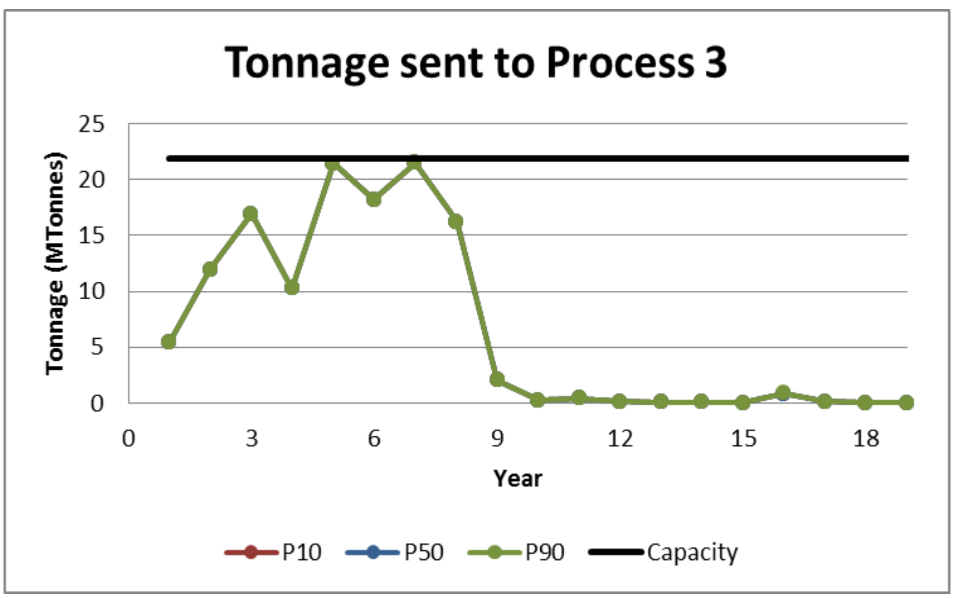

Figure 15: Tonnage input to Process 3.

destination. A given material type sent to a wrong destination may produce a very high cost with low or negligible recoveries, which are specified by material types and destinations in the parameter file. The way the algorithm controls misclassification errors is by maximizing the objective function, given that misclassification errors are very costly. The amounts of material type 3, 4 and 5 sent to stockpile are marginal and may be generated from misclassification; however, the algorithm will send that material to a particular destination if there is some profit associated. By having a look at the output material from the stockpiles, it was observed that only ore types 1 and 2 are rehandled and sent to process 1.

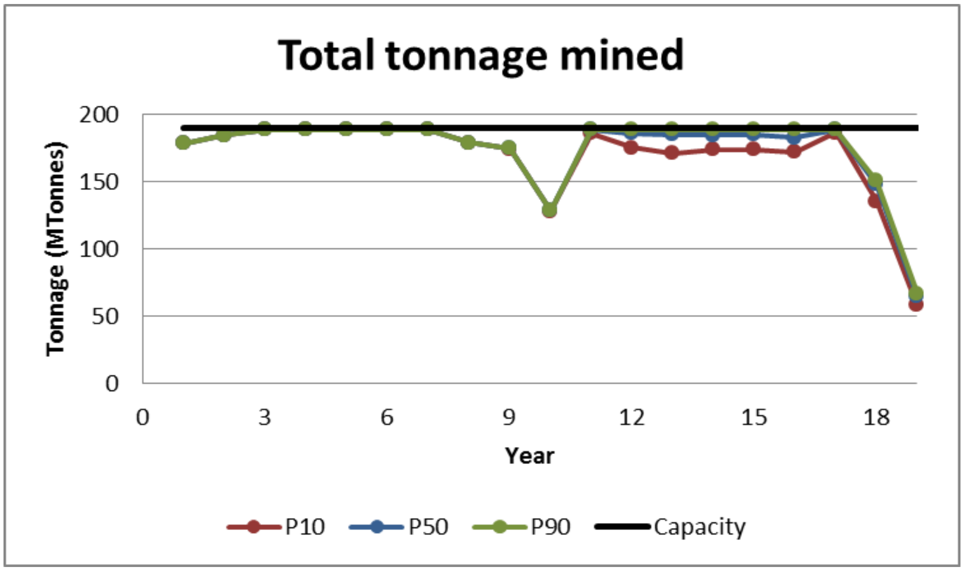

Figure 16: Total tonnage mined.

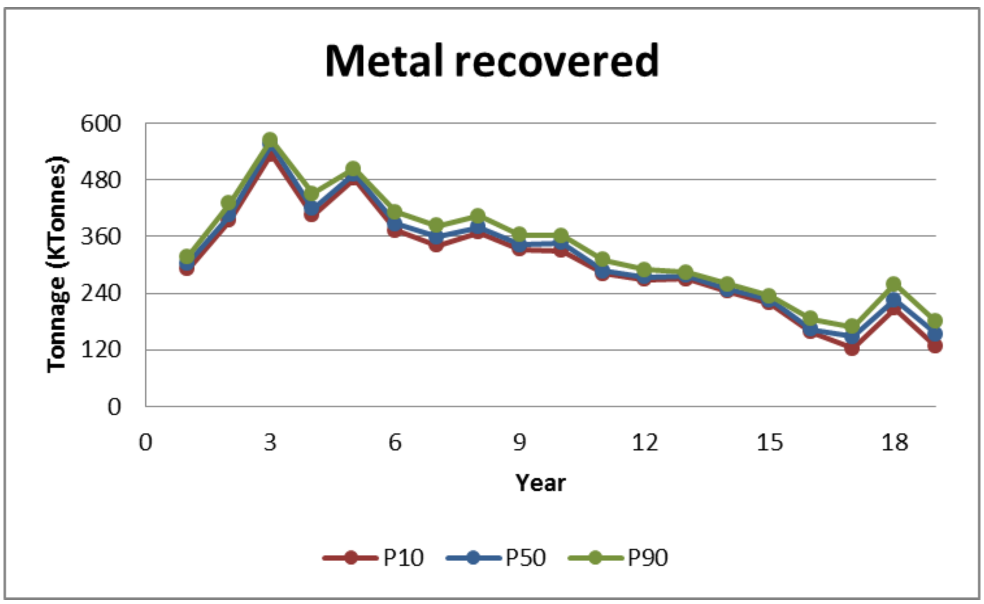

Figure 17: Metal recovered.

Figure 19 shows the P10, P50 and P90 of the cumulative discounted cash flows. It is observed that during the first two decades of the project, the expected NPV is around $7.8 billion. Although, no blending constraints were considered in this case study, the method attempts to maximize net present value expectations while maintaining target constraints within acceptable tolerable limits. It discriminates blocks between ore and waste based on the overall profitability; that is, the profit (or loss) obtained by sending a block to its best destination accumulated through the set of simulations. When profitable material cannot be processed due to target constraints, it is sent to the stockpiles for being rehandled in future periods.

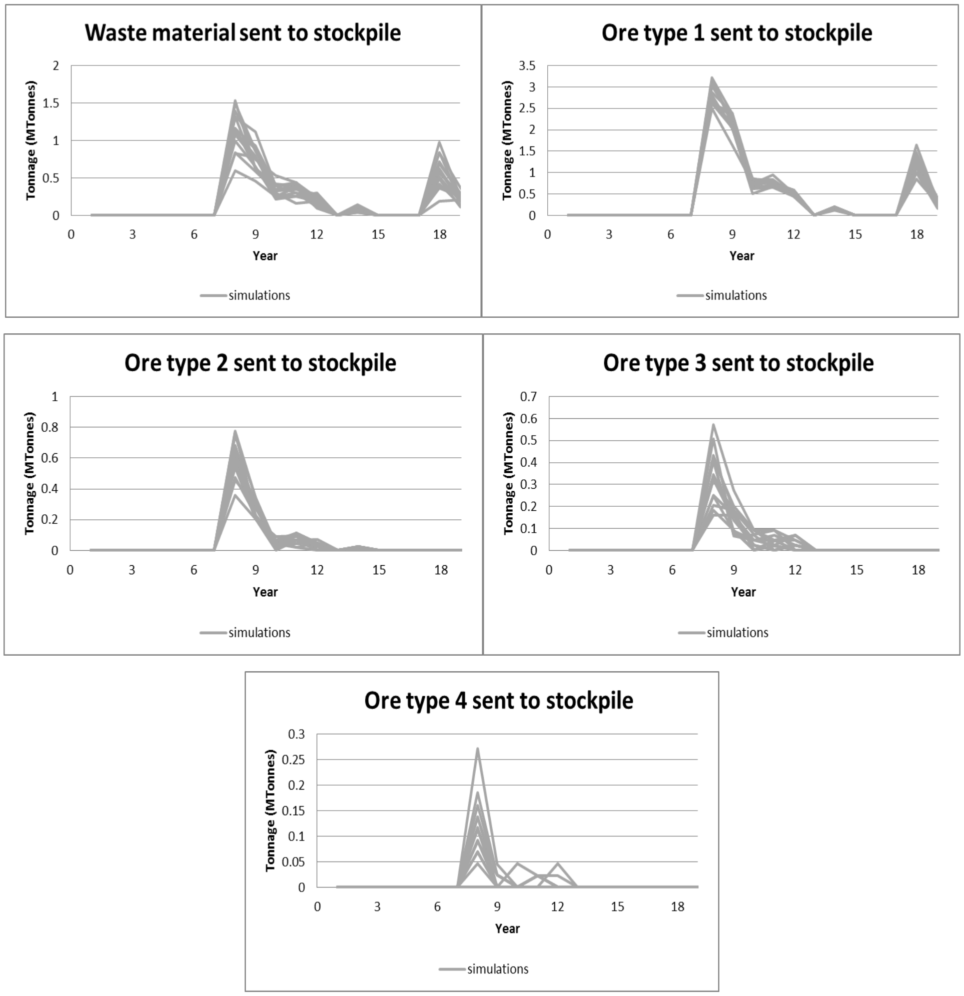

Figure 18: Material types sent to stockpile.

To evaluate the benefits of the method, a comparison with the initial solution that was generated conventionally can be performed. Figure 20 shows the tonnage sent to process 1 when using a conventional schedule. Large impractical deviations from the capacity of Process 1 can be observed.

Figure 21 shows the risk profile of the cumulative discounted cash of the conventional schedule. It is observed that during the first two decades of the project, the net present value expectations of the risk-based schedule are 30% greater than the conventional initial schedule. This shows the ability of the method to handle two conflicting objectives: maximize net present value expectations while approaching target constraints.

The method can handle processes with multiple processing options, additives and blending constraints. Although it shows good results in this particular case-study, its ability to handle complex blending requirements needs to be tested in a future work. Regarding the heuristic process, even though it has some flexibility to avoid getting trapped into local discontinuities of the deposit, new heuristic mechanisms and diversification strategies should be evaluated to better explore the solution space.

Figure 22 shows a cross section of the final schedule generated using the method. It can be observed that slope constraints are controlled by means of the correcting and checking mechanism utilized throughout the stages of the method.

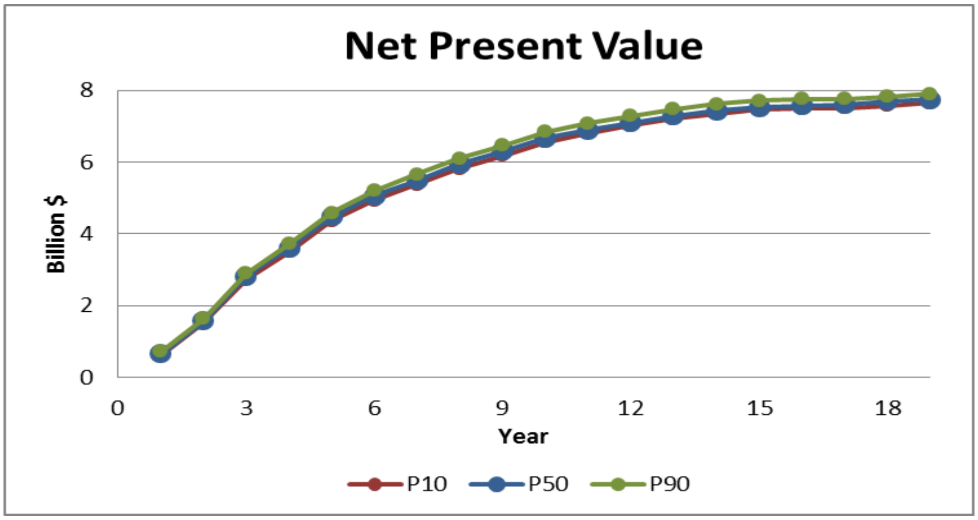

Figure 19: Net present value.

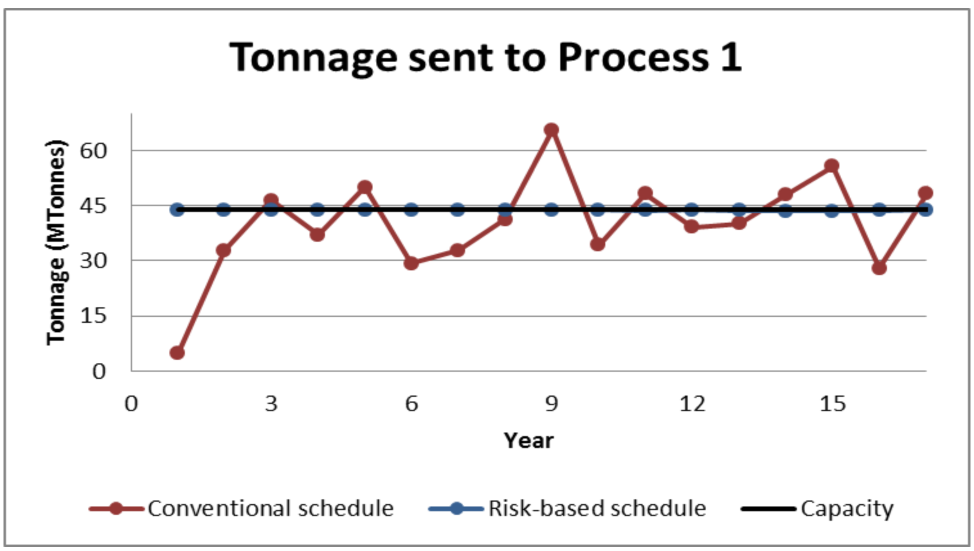

Figure 20: Process 1. Production forecast for the conventional initial solution.

4 Conclusions and Future Research Avenues

An iterative improvement heuristic method is presented for generating mine production schedules in single-pit mining complexes that can contain multiple metals or attributes, multiple material types, stockpiles and processing options. The method considers relaxed target constraints based on user-defined reliability levels. The implementation of the method in a copper deposit shows its ability to control target constraints by reducing the deviation from the capacity of Process 1 from 9% to 0.2% while maximizing project value expectations by increasing the expected net present value 30% when compared to the initial conventional solution.

An advantage of the method regarding previous developments is that it requires a single initial solution and the set of orebody simulations, whereas other implementations require multiple starting solutions, which increases substantially the labor of the mine planning engineer.

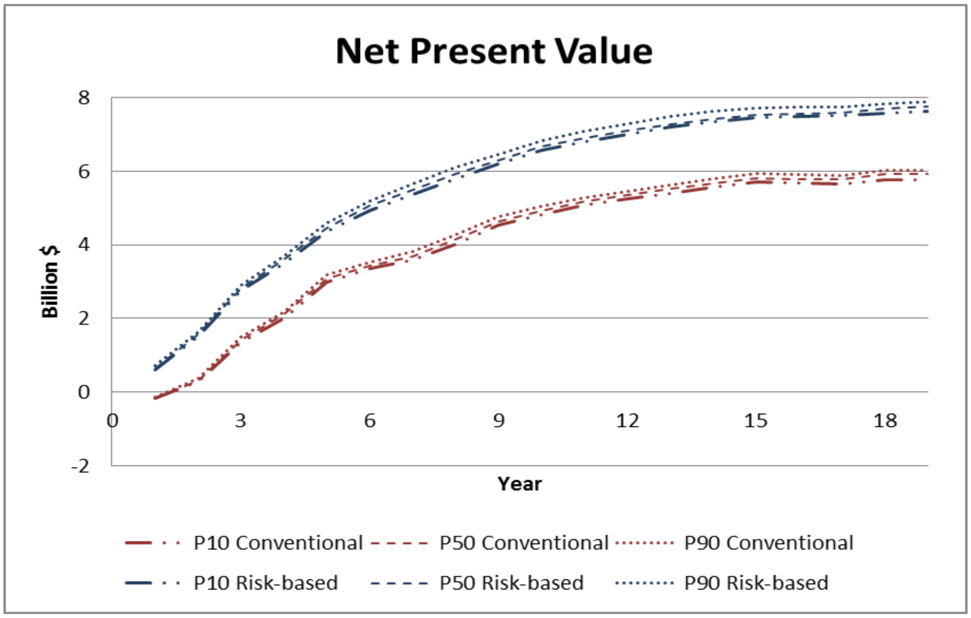

Figure 21: Net present value of the conventional initial solution.

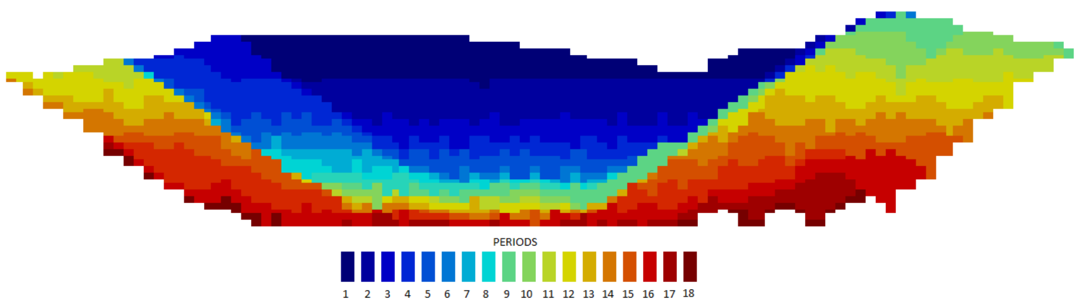

Figure 22: Cross-section of the risk-based schedule.

Regarding the NPV expectations, there were no significant additional benefits from increasing the number of simulations after 10. However, the amount of simulations required to control complex blending operations needs to be addressed in future implementations.

Although the method allows for improving an initial solution in terms of meeting target constraints and net present value expectations, different heuristic strategies with diversification should be implemented to explore better the solution space. Another possibility is to implement the method iteratively by considering several initial solutions simultaneously.

The possibility of adapting the method to multi-pit mining complexes is a future research avenue. Although the method requires practical amount of time for solving single-pit mining complexes (no more than 3 hours for dozens of millions of perturbations in a 1-million blocks deposit), its requirement in terms of computational time for multi-pit mining complexes needs to be addressed given the large size of the multi-pit problems.

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