Les Cahiers du GERAD ISSN: 0711–2440

Globally optimizing open-pit and underground mining operations under geological uncertainty

L. Montiel, R. Dimitrakopoulos,
K. Kawahata

G–2015–84

September 2015

GERAD HEC Montréal
3000, chemin de la Côte-Sainte-Catherine
Montréal (Québec) Canada H3T 2A7

Tél. : 514 340-6053
Téléc. : 514 340-5665
info@gerad.ca
www.gerad.ca

Globally optimizing open-pit and underground mining operations under geological uncertainty

Luis Montiel [a]
Roussos Dimitrakopoulos [a,b]
Kazuhiro Kawahata [a]

[a] *COSMO – Stochastic Mine Planning Laboratory, Department of Mining and Materials Engineering, McGill University, Montreal (Quebec) Canada, H3A 2A7*

[b] *and GERAD*

luis.montiel@mail.mcgill.ca
roussos.dimitrakopoulos@mcgill.ca
kazuhiro.kawahata@newmont.com

September 2015

Les Cahiers du GERAD

G–2015–84

Abstract: A method that optimizes mining complexes that are comprised of multiple processing destinations, open pits and underground operations is presented. Mining, blending, processing and transportation decision variables are simultaneously optimized while accounting for geological uncertainty. The method uses a simulated annealing algorithm at different decision levels to generate a stochastic-based extraction sequence and processing policies. A case study shows its ability to generate a higher net present value while facing a reduced amount of risk when compared to traditional optimization methods.

Key Words: Mining complex, simulated annealing algorithm, net present value.

Acknowledgments: We would like to thank the organizations and companies who funded this research: Canada Research Chairs (Tier I) in Sustainable Mineral Resource Development and Optimization under Uncertainty, and NSERC Collaborative Research and Development Grant CRDPJ 411270–10, entitled 'Developing new global stochastic optimization and high-order stochastic models for optimizing mining complexes with uncertainty'; industry collaborators: AngloGold Ashanti, Barrick Gold, BHP Billiton, De Beers, Newmont Mining and Vale, and NSERC Discovery Grant 239019. Particular thanks to Mern Vatcha from Barrick for his generous contribution.

1 Introduction

A mining complex is a value chain with multiple components: deposits, stockpiles, processing destinations and transportation systems. Optimizing a mining complex demands the simultaneous optimization of all its components. This problem is known in the mining literature as global optimization of mining (Whittle 2007, 2010). Several methods have been developed to incorporate multiple components of the value chain during the optimization. Hoerger et al. (1999) formulate the problem of optimizing the simultaneous mining of multiple pits and the delivery of ore to multiple plants as a mixed integer program. The model groups blocks into increments and accounts for multiple stockpiles. The authors implement the model at Newmont's Nevada operations where 50 sources, 60 destinations and 8 stockpiles are present, and it leads to an increase of profitability by taking advantage of the synergies. Stone et al. (2007) present the Blasor optimization tool developed by the mine planning optimization group within BHP Billiton. Blasor formulates the problem of determining the optimal extraction sequence of multiple pits as a mixed integer linear program and solves it using ILOG CPLEX (IBM, 2011). Blasor aggregates spatially connected blocks that have similar properties (Menabde et al., 2007) and generates near-optimal solutions in practical times in large-scale operations: Yandi (1000 aggregates, 11 pits and 20 periods) and Illawarra Coal mine (eight domains) (Rocchi et al. 2011). Zuckerberg et al. (2007) present Blasor-InPitDumping, which is an extension of Blasor that accounts for waste handling; that is, it incorporates refilling mined-out areas with waste. Zuckerberg et al. (2011) introduce Bodor to optimize the sequence of extraction of bauxite 'pods' at Boddington bauxite mine in south-western Australia. Pods are distinct bodies of modest-sized ore that are lying close to the surface. Chanda (2007) formulates the delivery of material from different deposits to a metallurgical complex as a network linear programming optimization problem. The model attempts to minimize the costs through the network that encompasses mines, concentrators, smelters, refineries and market regions. Wooller (2007) describes the software COMET, which is used to optimize mill throughput/recovery and cut-off grade. COMET uses an iterative algorithm to define operating policies and process routes (eg heap leach versus concentration). Whittle (2007) introduces the global asset optimization tool incorporated in Whittle software. The tool is designed to optimize the sequence of extraction of multiple deposits considering complex processing and blending operations.

The methods described in the previous paragraph ignore the uncertainty associated with different parameters. Groeneveld et al. (2010) incorporate uncertainty in market price, costs, utilization of equipment, plant recovery and time for building options (infrastructure) while simultaneously optimizing mining, stockpiling, processing and port policies. Bodon et al. (2010) model the problem of supplying exports in a coal chain as a discrete event simulation model. The model is able to asses various operating practices, including maintenance options and capital expenditure, to determine the best infrastructure for a given system. In both methods, geological uncertainty is discarded, which is the major contributor of not meeting production targets and net present value (NPV) forecasts.

Although efficient and able to incorporate several components of the value chain, the methods available in the technical literature have at least one of the following limitations when globally optimizing mining complexes:

- some decisions are fixed when they should be dynamic (operating modes, destinations of mining blocks, etc)
- component-based objectives are imposed, which may not coincide with global objectives
- many parameters are assumed to be known when they are uncertain (Whittle 2007).

Several methods have been used to incorporate geological uncertainty for the open pit production scheduling problem (Albor and Dimitrakopoulos, 2009, 2010; Dimitrakopoulos and Ramazan, 2004; Godoy, 2003; Lamghari and Dimitrakopoulos, 2012; Lamghari et al., 2013; Leite and Dimitrakopoulos, 2007). However, little work has been done regarding the production scheduling of underground mines. Grieco and Dimitrakopoulos (2007) implement probabilistic programming in stope design optimization. They evaluate the probabilities of the different rings of being above specified cut-offs. However, the probabilistic programming formulation discards the compound relationship between rings, whereas stochastic formulations make full use of joint local uncertainty.

This paper describes a method for simultaneously optimizing different components of a mining complex comprised of open pits and underground operations under geological uncertainty. The method is described in the next section, its implementation at a gold complex is then displayed and, finally, conclusions are presented.

2 Optimizing the components of the value chain

2.1 Preliminaries

The components of a mining complex are strongly interrelated (Figure 1). Any decision taken in a particular component affects the decisions taken at the others. To optimize a mining complex the different components must be optimized simultaneously.

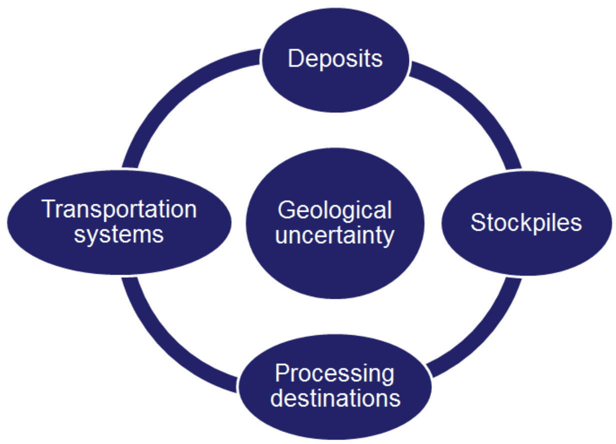


Figure 1: Components of a mining complex.

Mineral deposits are the sources of material. Different types of ore are extracted via open pits or underground mining methods. Open pits are discretised into mining blocks whereas underground mines are comprised of development, preparation and production activities. Different underground mining methods have different activities; however, regardless of the mining method, the mine design can be discretised in activities and dependencies. That is, each activity has a set of successor and predecessor activities, similar to slope constraints in an open pit.

Mining blocks in open pits and activities in underground mines are named as 'units' in this paper. Each unit can be sent to a particular processing destination or a stockpile. There may be as many stockpiles as metallurgical ore types available from the deposits. Stockpiles contain potential ore, contribute to the blending operation and serve as a backup supply of material.

Each processing destination may have operating modes that determine the operating costs, metallurgical recoveries, operational blending limits for the metallurgical properties and throughputs. For example, the capacity, operating cost and recovery of a milling plant change if it operates to generate fine (80μm) or coarse material (120μm). The choice of operating mode at a processing destination should be made by accounting for the decisions taken at the other components of the value chain. In some cases, the quality of the material extracted from different deposits does not meet the specific blending requirements at a given processing destination. To meet the quality targets, external blending materials are added to specific destinations (Figure 2). These materials come from external sources and have very specific qualities. For example, in an autoclave, external material with high sulphide and low carbonate may be added to meet the SS/CO_3 ratio if the ore extracted from the deposits have low sulphide.

The output material from the processing destinations is transported to final stocks or ports using available transportation systems (Figure 3). It is important to account for transportation systems when optimizing

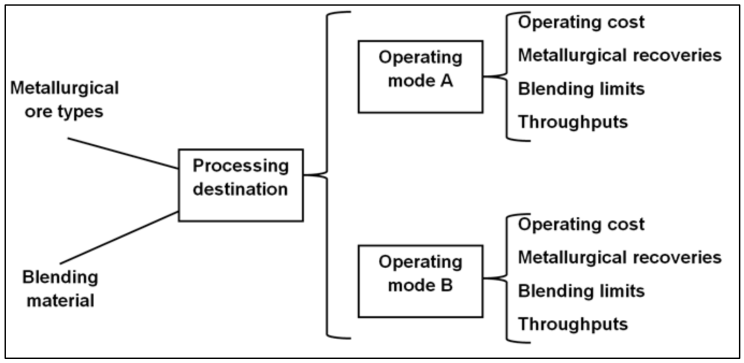


Figure 2: Processing destination.

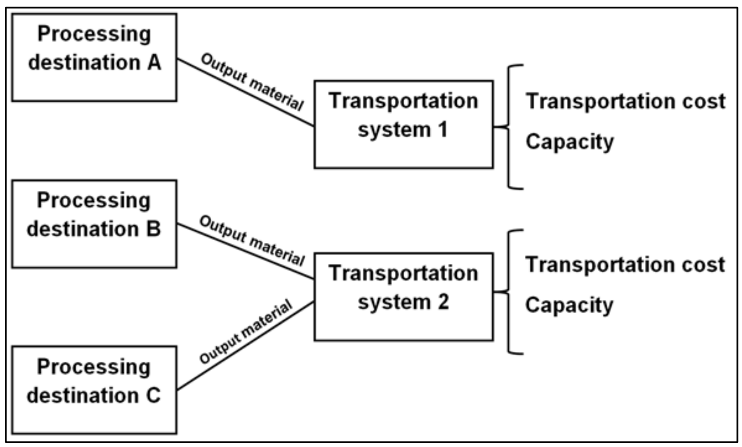


Figure 3: Transportation systems.

a mining complex given that they can limit the overall throughput of the system (bottleneck). Each transportation system has an associated cost and capacity.

2.2 Mathematical model

The goal is to maximize expected NPV while minimizing deviations from targets associated with the different components of the value chain. The objective function (Eq. 1) has two terms: *discprofit(s,t)* is the discounted profit in period t under scenario s and *penalty(s,t)* is a term that accounts for the penalized deviations from the targets at different components in period t under scenario s. Each scenario is a combination of orebody simulations of the deposits.

$$maximize\ O = \sum_{s=1}^{S}\sum_{t=1}^{T}\left(discprofit\left(s,t\right) - penalty\left(s,t\right)\right) \tag{1}$$

The discounted profit at each period and scenario is calculated by accounting for the revenue obtained by selling the different products, the cost of mining at all deposits, the cost of processing the material at all destinations, the cost of stockpiling the material, the cost of sending material from the stockpiles to the available processing destinations and the transportation costs.

$$\begin{aligned} discprofit\left(s,t\right) = revenue\left(s,t\right) - minecost\left(s,t\right) - procost\left(s,t\right) \\ - stockcost\left(s,t\right) - rehandlecost\left(s,t\right) - transcost(s,t) \end{aligned} \tag{2}$$

The second term of the objective function, $penalty(s,t)$, accounts for the penalized deviations, and is evaluated as:

$$penalty\,(s,t) = penalmine\,(s,t) + penaltrans\,(s,t) + penalpro\,(s,t) + penalmetal(s,t) \tag{3}$$

where *penalmine(s,t)* are the penalized deviations from the capacities of the different mines, *penaltrans(s,t)* are the penalized deviations from the capacities of the different transportation systems, *penalpro(s,t)* are the penalized deviations from the capacities at the different processing destinations and *penalmetal(s,t)* are the penalized deviations from the operational ranges of some operational properties.

Three sets of decision variables are used to evaluate revenues, costs, production and deviations at the different components of the value chain. X_{itd} is a binary variable that represents whether or not a particular unit i is mined in period t and sent to processing destination d. Y_{tdo} is a binary variable that represents whether or not an operating mode o is used in destination d during period t. Z_{tdr} represents the proportion of output material from destination d transported using transportation system r during period t.

The following equations show the evaluation of tonnages at different components using these decision variables:

$$mineproduction\,(s,t) = \sum_{i=1}^{I}\sum_{d=0}^{D} X_{itd} \cdot m_{is} \tag{4}$$

$$tonneoutprocess\,(s,t,d) = \sum_{o=1}^{O(d)} (tonneprocess(s,t,d) \cdot Y_{tdo} \cdot P_{do}) \tag{5}$$

$$tonnetransport\,(s,t,r) = \sum_{d=1}^{D} (tonneoutprocess(s,t,d) \cdot Z_{tdr}) \tag{6}$$

The amount of material extracted from the deposits can be evaluated using Eq. 4, the output material from a given destination can be evaluated using Eq. 5 and the amount of material transported using a particular transportation system can be evaluated using Eq. 6. I is the set of all units from the deposits, D is the set of processing destinations, *mis* is the tonnage of unit i under scenario s, *O(d)* is the set of operating modes available at destination d, *tonneprocess(s,t,d)* is the tonnage sent to destination d from the deposits and the stockpiles in period t under scenario s, and P_{do} is the proportion output/input tonnage in destination d using operating mode o.

A mining complex may contain a large number of units which leads to a complex optimisation model that is hard to solve. Hence, it is necessary to find solution methods that overcome this limitation.

2.3 Solution

Any solution of the optimization model must answer the following questions associated with the three main sets of decision variables:

1. Which units are going to be extracted in each period and where are they going to be sent (X_{itd} variables)?
2. Which operating modes are going to be used at the different processing destinations (Y_{tdo} variables)?
3. Which transportation systems are going to be used (Z_{tdr} variables)?

Given a particular solution, it is possible to modify the objective value by generating perturbations at the three different decision levels. These perturbations should be done towards improvements in the objective value. Given the monetary value associated with time due to discounting, profitable units should be extracted in early periods and non-profitable ones should be pushed to later periods. Operating and transportation decisions should minimize processing and transportation costs and deviations.

2.3.1 The perturbation mechanism

For each unit u, it is possible to calculate the cumulative profit of u in every destination by accumulating the economic value in each scenario (Figure 4). The cumulative profit provides guidance as to the most profitable destinations for a particular unit and controls the iterating process when swapping periods and destinations of a mining unit (Figure 5). If the greatest cumulative profit of a unit is positive, extracting that unit in an earlier period will be favored; otherwise, the iterating process will favor extracting the unit in a later period.

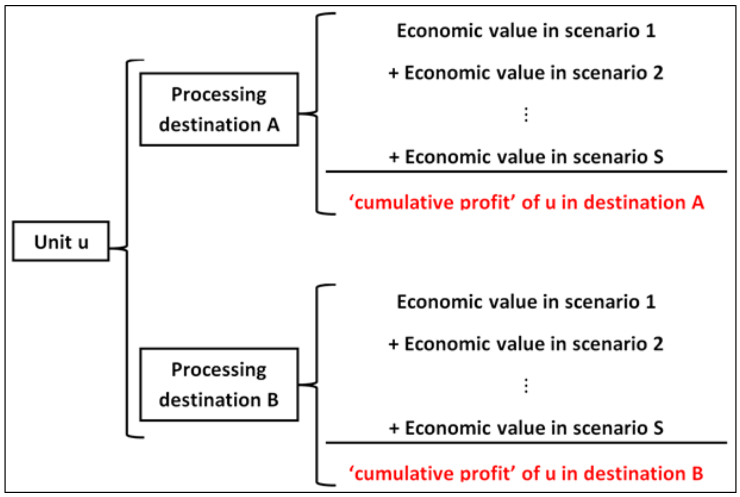


Figure 4: Cumulative profit of a unit.

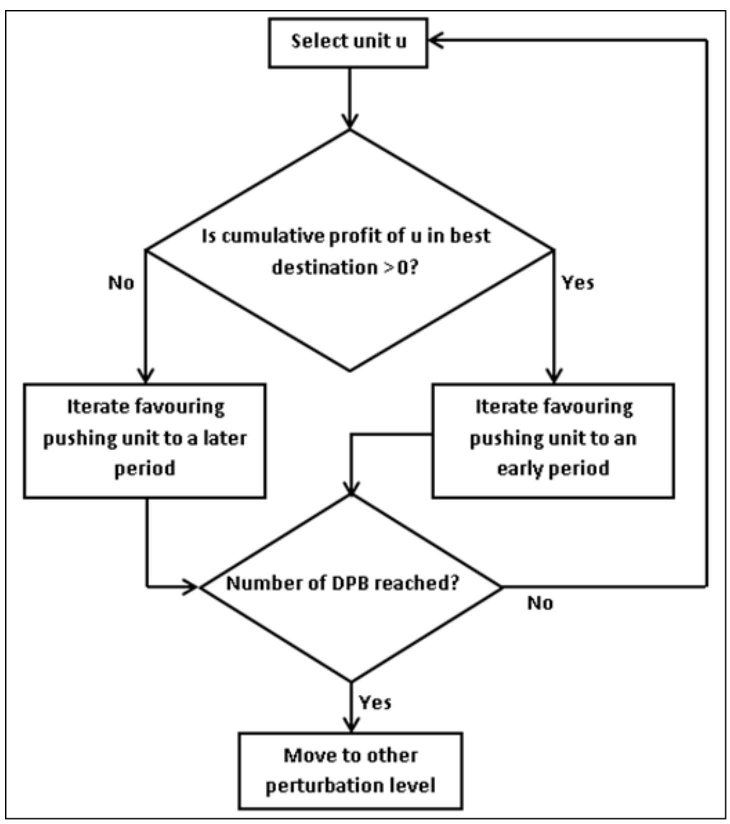


Figure 5: Perturbation of units.

The candidate destinations include the destinations with positive cumulative profit if the unit is profitable or the less unprofitable destination in the opposite case.

The iteration process over the candidate periods and destinations of a mining unit is designed to increase the expected NPV given the time value of money. However, the objective value of the perturbed solution is also affected by the penalized deviations. Therefore, there might be cases when pushing a profitable unit to a later period or an unprofitable one to an earlier period increases the objective value given the lower deviations in the new solution. In these cases, the objective function can be seen as trade-off between maximizing the expected NPV and minimizing the penalized deviations.

The perturbations at an operating decision level consist of swapping operating modes at different processing destinations towards improvements in the objective value. The perturbations at the transportation decision level consist of modifying the transportation proportions of the output material from the different processing destinations; for example, changing the transportation of the output material from a mill from 50% trucks / 50% pipeline to 70% trucks / 30% pipeline. The transportation perturbation mechanism seeks to minimize transportation costs and deviations.

At any level, perturbations are accepted or rejected using Eq. 7 from the Metropolis algorithm (Metropolis et al., 1953; Kirkpatrick et al., 1983).

$$P\left(\triangle O\right) = P\left(O_{new} - O_{curent}\right) = \begin{cases} 1 & if\ \triangle O \geq 0 \\ e^{\frac{-\triangle O}{T}} & otherwise \end{cases} \tag{7}$$

where T is the annealing temperature. The probability of accepting an unfavorable perturbation is greater at higher temperatures. As the optimization proceeds, the temperature is gradually lowered by a reduction factor. When the temperature approaches zero, the probability of accepting an unfavorable swap tends to zero. This allows the algorithm to converge to a final solution.

2.3.2 The method

The method proposed to optimize a mining complex has three stages (Figure 6). The first stage consists of assigning periods and destinations to the mining units from an initial solution. In the second stage the method evaluates the profits, productions and deviations at the different scenarios. It also evaluates the cumulative profit of the mining units at the different destinations. The last stage is the perturbation mechanism at the three different decision levels. The algorithm stops when it reaches a user-specified number of iterations or poor improvement is presented in the objective value after a certain number of perturbations.

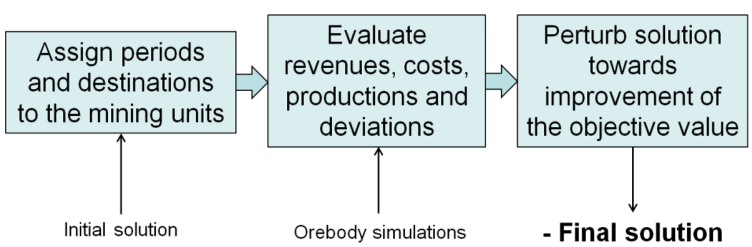


Figure 6: Method.

3 Case study: A gold operation

The method is implemented at a gold complex comprised of one open pit and one underground mine (Figure 7). Higher-grade oxide ore is processed at a mill, while lower-grade material is treated on heap leach pads. Refractory ore is processed at one autoclave. The open pit provides both oxide and refractory ore, whereas the underground mine just provides refractory ore for the autoclave.

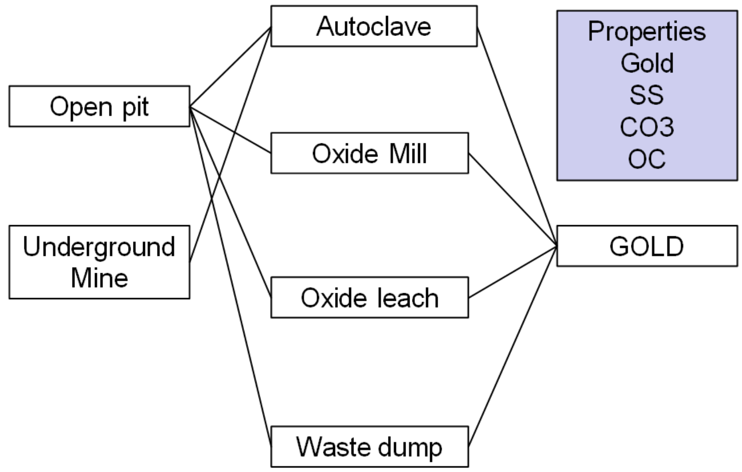


Figure 7: Gold complex.

Twenty orebody simulations for gold, sulphide sulphur, CO_3 and organic carbon are provided for the open pit. The higher concentrations of gold are located in the north-east part of the deposit, where the current mining phases are located (Figure 8). The gold and sulphide sulphur grades are controlled by the mineralized domains, whereas the carbonate and organic carbon are spread in all the areas of the deposit.

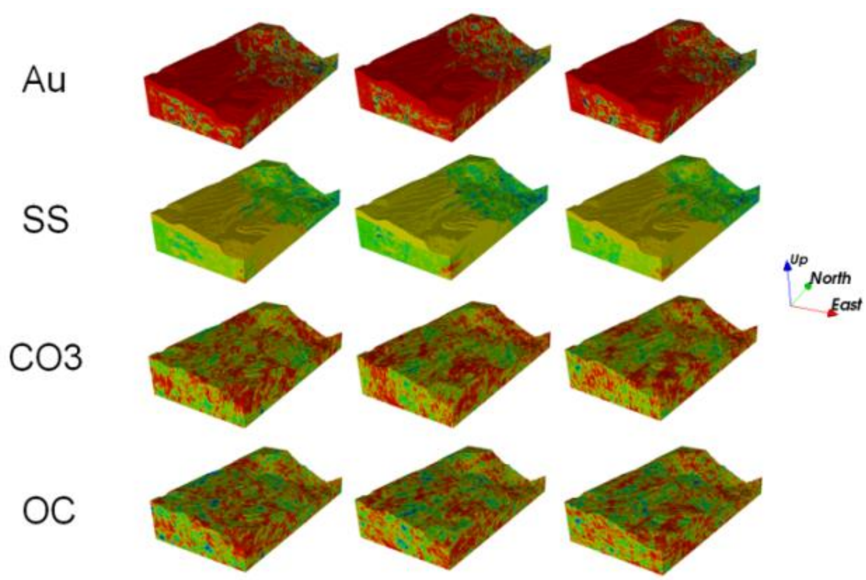


Figure 8: Three orebody simulations of the open pit,

The underground mine uses underhand-cut-and-fill due to the relatively low rock quality in the ore zones. Intensity of gold mineralization is related to structural complexity and the location of rocks chemically receptive to mineralization. The production zones are located in the high-grade areas (Figure 9).

Twenty orebody simulations are generated for the underground deposit using direct block simulation by considering the drillhole data within the mineralized domain (Godoy 2003). Figure 10 shows the validation of the generated orebody simulations. It can be observed that the simulations respect the statistics of the drillhole data as they reproduce its histograms and variograms at the main directions of anisotropy. The simulated values at each unit are calculated by averaging the simulated points that fall inside. That is, given the different shapes and sizes of the underground mining units, there is no single support size as in the open

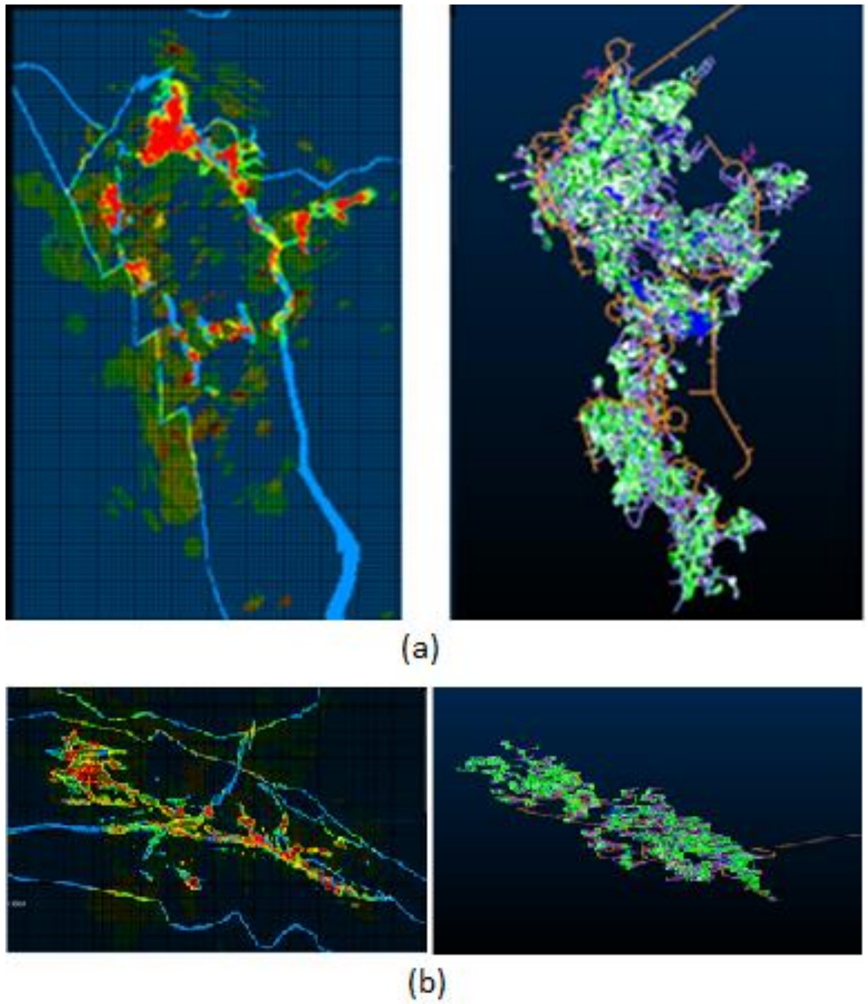


Figure 9: Gold grades (left) and production zones (right) in the underground mine: (a) Plan view; (b) Cross section.

pits, where the mining blocks have the same size. Figure 11 shows three different orebody simulations and the production zones of the mine.

The autoclave has tight operating ranges for SS/CO_3, SS, CO_3 and organic carbon. To help metallurgical blending, concentrates from other plants are added to the process (Figure 12).

In the three processing destinations, the metallurgical recovery of gold follows non-linear curves. In the autoclave, the recovery curve is a function of the gold grades and the organic carbon, whereas in the oxide mill and the heap leaching plant, the recovery is a function of gold grades only.

3.1 Initial solution

An initial solution for the optimization of the gold complex was generated by:

- considering the current mining plan in the underground mine that was developed by the mine planners using Enhanced Production Scheduler software
- using Milawa scheduler in Whittle software for the open pit using the e-type of the orebody simulations; that is, the average grades of the mining blocks from the different realizations.

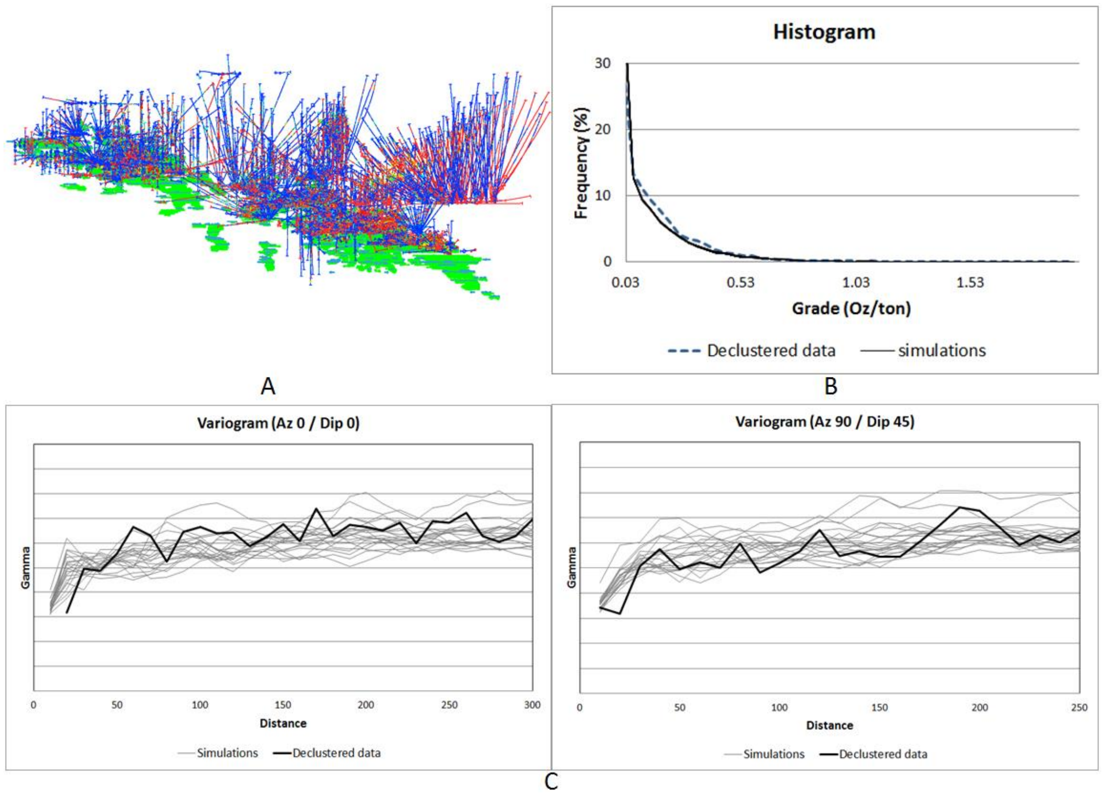


Figure 10: Validation of the simulations in the underground mine: (a) Drillhole data; (b) Histogram reproduction; (c) Variogram reproduction.

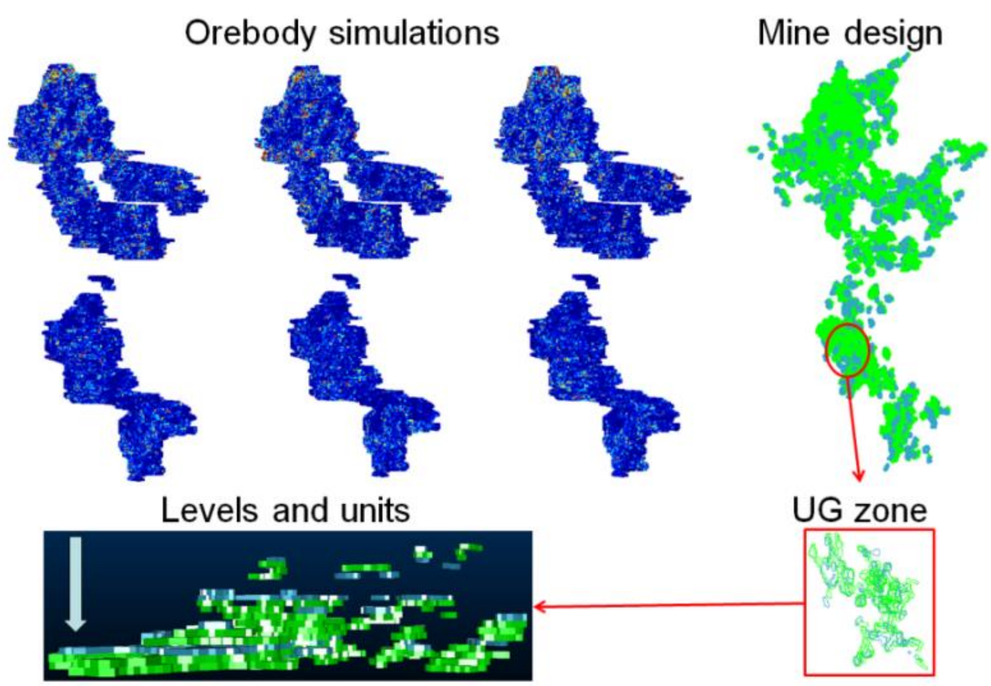


Figure 11: Orebody simulations and production zones of underground mine.

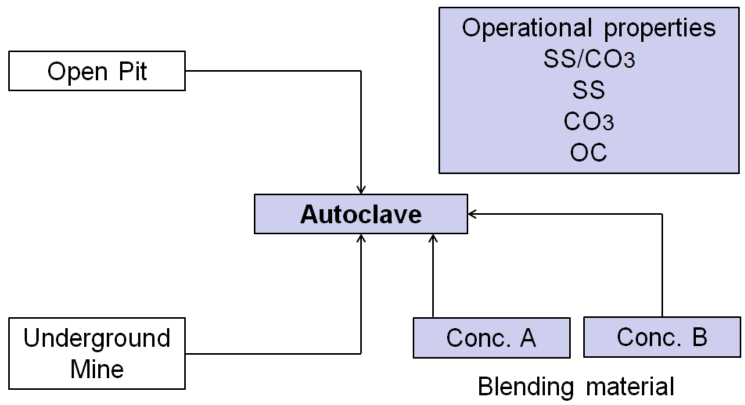


Figure 12: Autoclave.

The amount of external blending material used in the autoclave is considered when evaluating the results of the implementation of the initial solution over the different scenarios (combinations of orebody simulations of both deposits). The productions of the two mines, the autoclave and the oxide mill are shown in Figure 13. It can be observed that the underground mine operates below the capacity, whereas the open-pit operates very close to its capacity until the depletion of the reserves. Although external blending material is added to the autoclave, given the tight blending constraints imposed to this processing destination, the conventional scheduler can only find blended material to fill the capacity in three periods of the life-of-mine (LOM). There is a significant shortfall in production in the autoclave in year 4, and after year 9, the tonnage sent to this processing destination is very marginal. Regarding the oxide mill, the production is going to be close to capacity in years 2-4, but deficient production is observed in the rest of the periods of the LOM. However, most of the oxide ore filled to this processing destination comes from another pit that is not considered in this study.

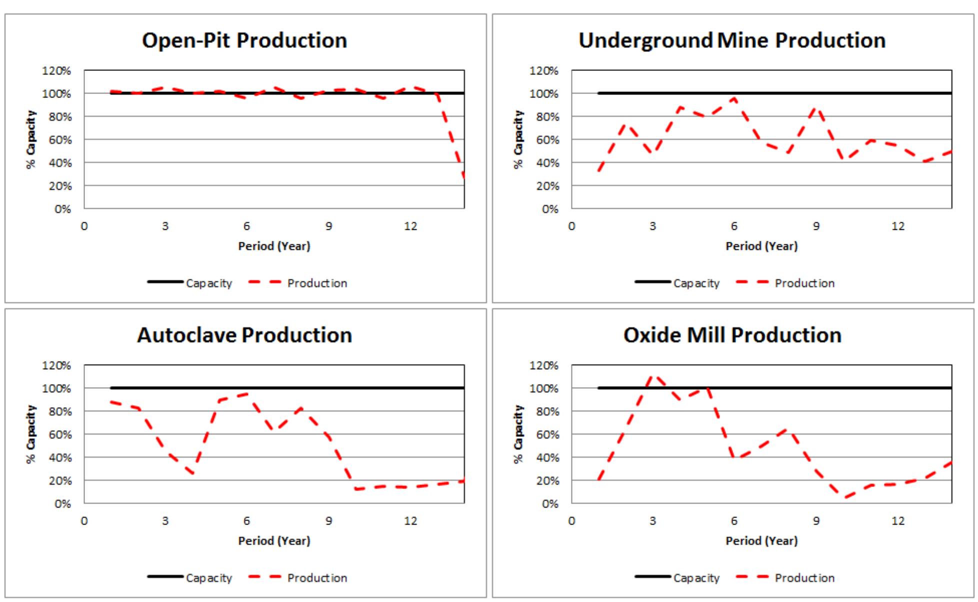


Figure 13: Productions with the initial solution.

The SS is below the operational ranges in most of the years, whereas the SS/CO_3 ratio falls below the operational ranges in the last years (Figure 14). The CO_3 increases with time and falls inside the operational ranges in most of the years. The organic carbon is well controlled in all the different scenarios.

The risk profile of the NPV is displayed in Figure 15. It is observed that after year 9, the cumulative NPV starts to decrease given the marginal tonnage sent to the autoclave. It will be more profitable to stop the operation after year 9. However, there is another pit that is not considered in this study, which can add more years of profitable operation.

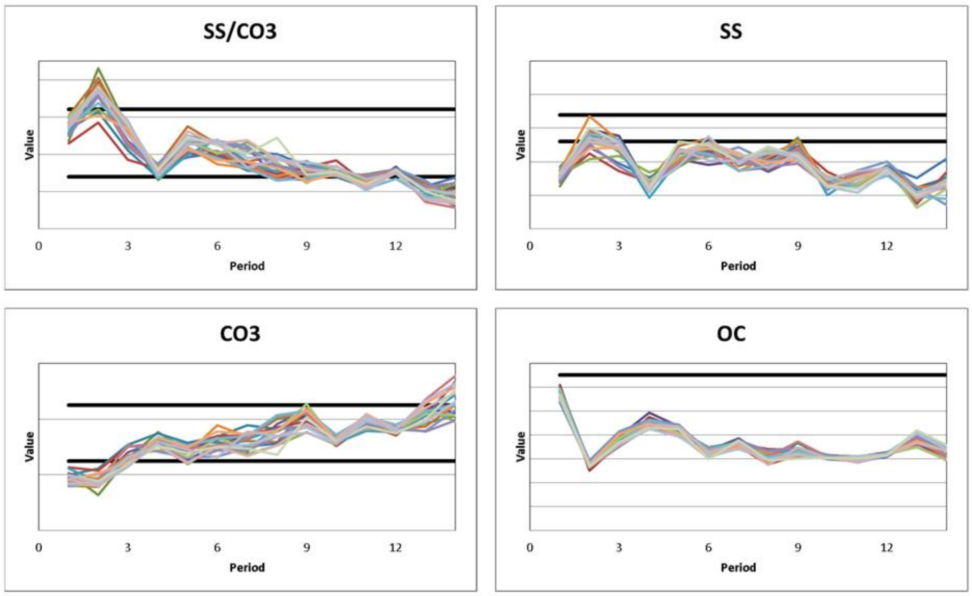


Figure 14: Operational properties with the initial solution.

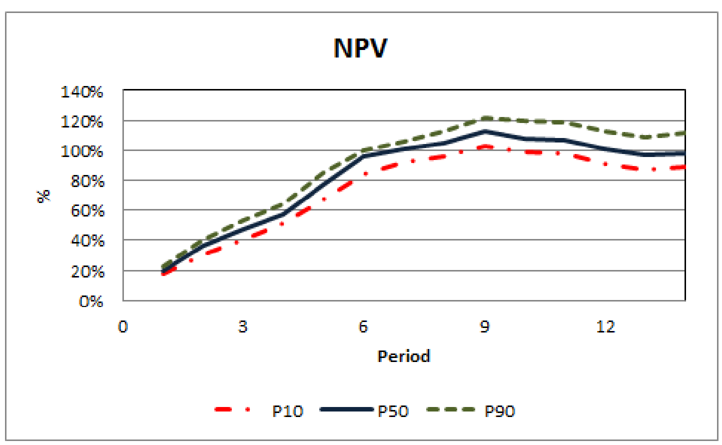


Figure 15: NPV with the initial solution.

3.2 Optimization parameters

Different tests are performed to define the optimization parameters that lead to the largest improvement of the objective value. Different initial temperatures, reducing factors and the number of perturbations were evaluated. Figure 16 shows the evolution of the objective value with the number of perturbations for six different initial temperatures. The largest improvement in the objective value is obtained with an initial temperature of the order of 1 million.

Other important parameters to define are the per-unit penalty values associated with the targets at the different components. The magnitude of the penalties must be defined so as to balance the two terms of the objective function. If the penalty values are too high, the reproduction of the targets will be largely improved, ignoring the first term of the objective function and generating poor improvement of expected NPV. Conversely, if the penalty values are too small, they will generate impractical solutions with large and non-realistic NPV forecasts given the large violations of the targets.

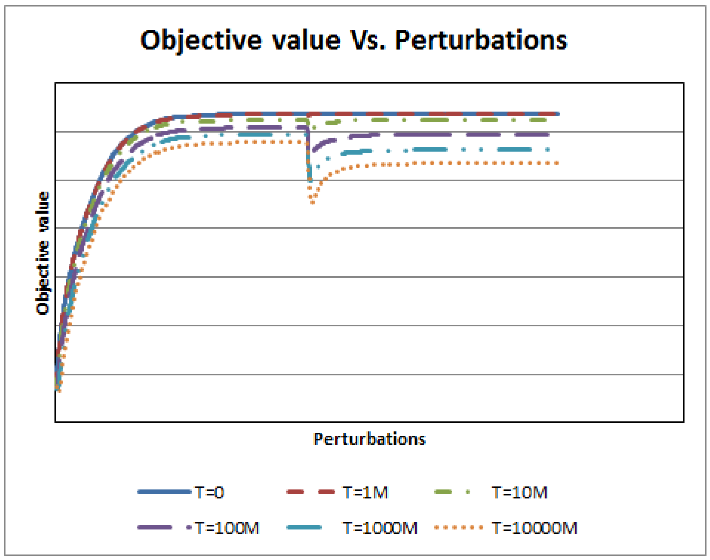


Figure 16: Evolution of the objective value with different temperatures.

3.3 Stochastic solution

The method is next implemented after setting up the optimization parameters. It is possible to observe from Figure 17 that the solution asks for the underground mine to be operated very close to its target, except in year 12 where there is a significant shortfall. However, the productions at the autoclave and the oxide mill are below their capacities in all the periods of the LOM. Regarding the blending properties, a similar behaviour is observed when compared with the deterministic initial solution (Figure 18). Given the low sulphide sulphur presented in the simulations, the method is not able to accommodate the sulphide sulphur inside the operational ranges. The expected NPV is 14% greater than the one obtained with the deterministic initial solution (Figure 19).

The method is implemented considering different amounts of external blending material input to the autoclave. In particular, the amount concentrate A fed to the autoclave is increased five times given its high sulphide sulphur. The productions at the underground mine and the autoclave and the sulphide sulphur with the new stochastic solution are displayed in Figure 20. It can be observed that by increasing the amount of concentrate A, the method is able to find more material to blend in order to increase the production in the autoclave. Furthermore, the sulphide sulphur approaches the operational ranges by increasing the external blending material given its large sulphide sulphur content compared to the material extracted from the deposits. However, the content of sulphide sulphur is still below the operational ranges given the low grade in the orebody simulations.

The expected NPVs of both stochastic solutions are very similar (Figure 21). However, the availability of concentrate A is a strong assumption. The shortfall in production in the autoclave in year 4 in both stochastic solutions suggests that the method got trapped in a local optimum. To overcome this situation, a diversification strategy in the perturbations at the unit decision level is desired.

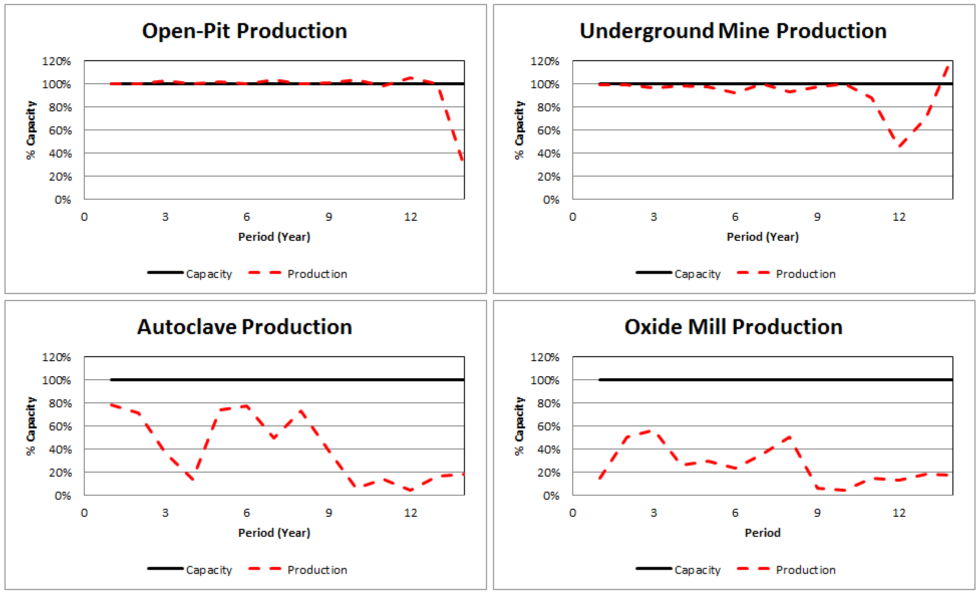


Figure 17: Productions with the stochastic solution.

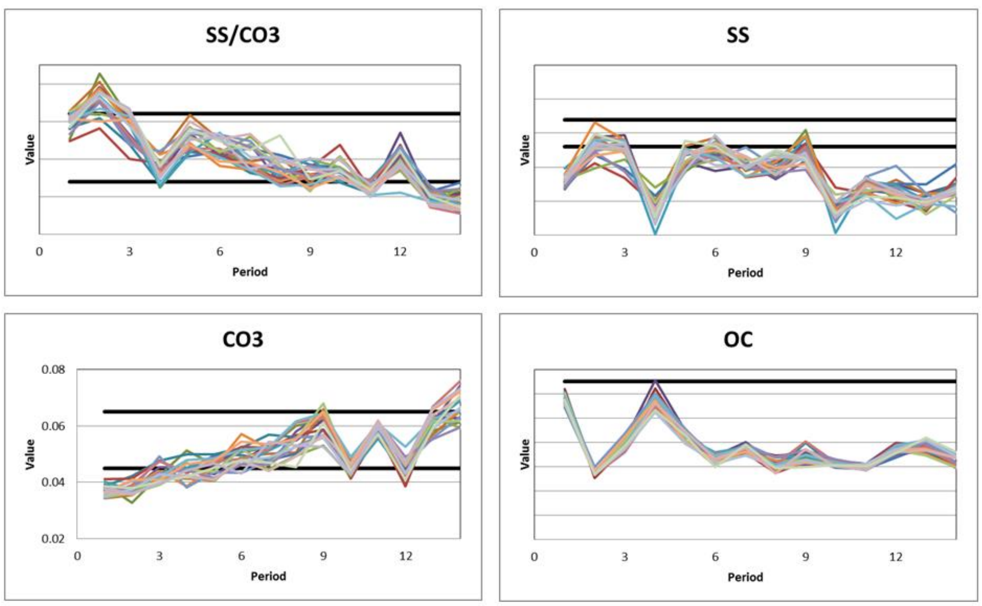


Figure 18: Operational properties with the stochastic solution.

A better control of the operational ranges and the capacity of the autoclave are obtained with the stochastic approach when considering a set of initial stockpiles. These results are displayed in Appendix A.

4 Conclusions

This paper presents a method to simultaneously optimize different components of mining complexes comprised of open pits and underground operations. The method can be easily adapted to different underground mining methods.

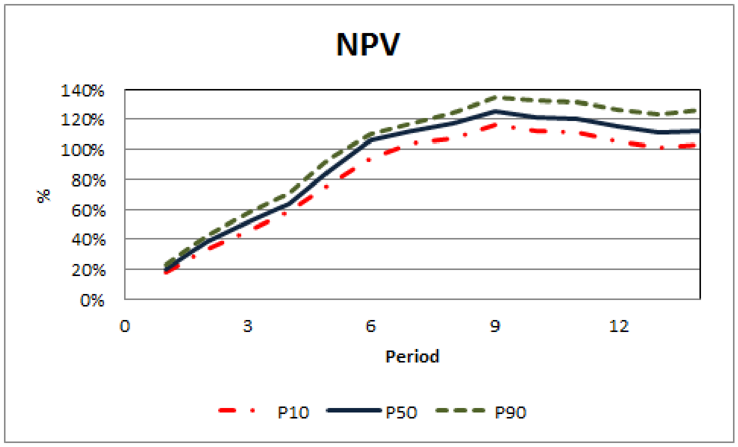


Figure 19: NPV with the stochastic solution.

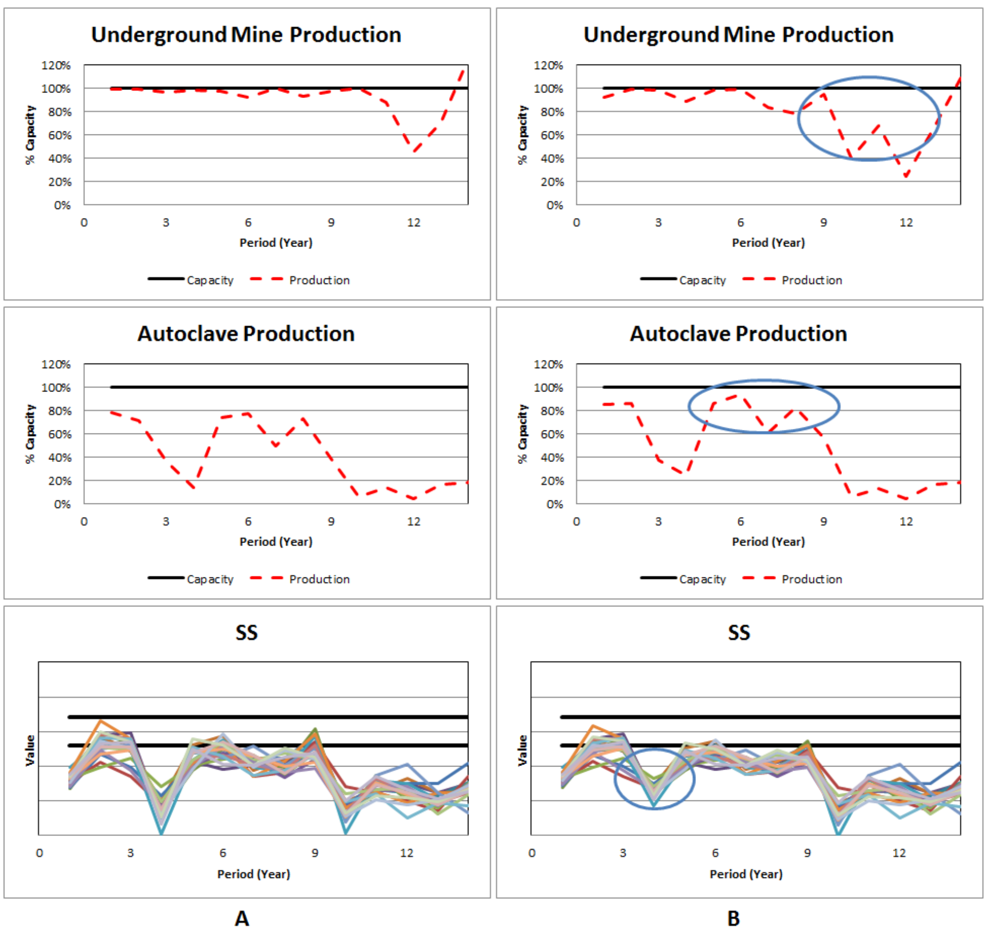


Figure 20: Productions with the new stochastic solution: (a) Concentrate A; (b) Concentrate A x 5.

At the different processing destinations, the method accounts for operating modes and external sources of material used for blending purposes. The implementation of the method at a gold mining complex shows substantial improvement in expected NPV and in meeting operational targets for the autoclave.

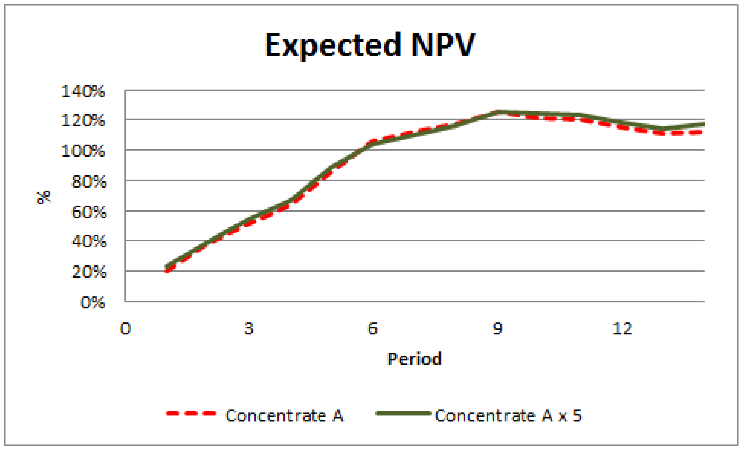
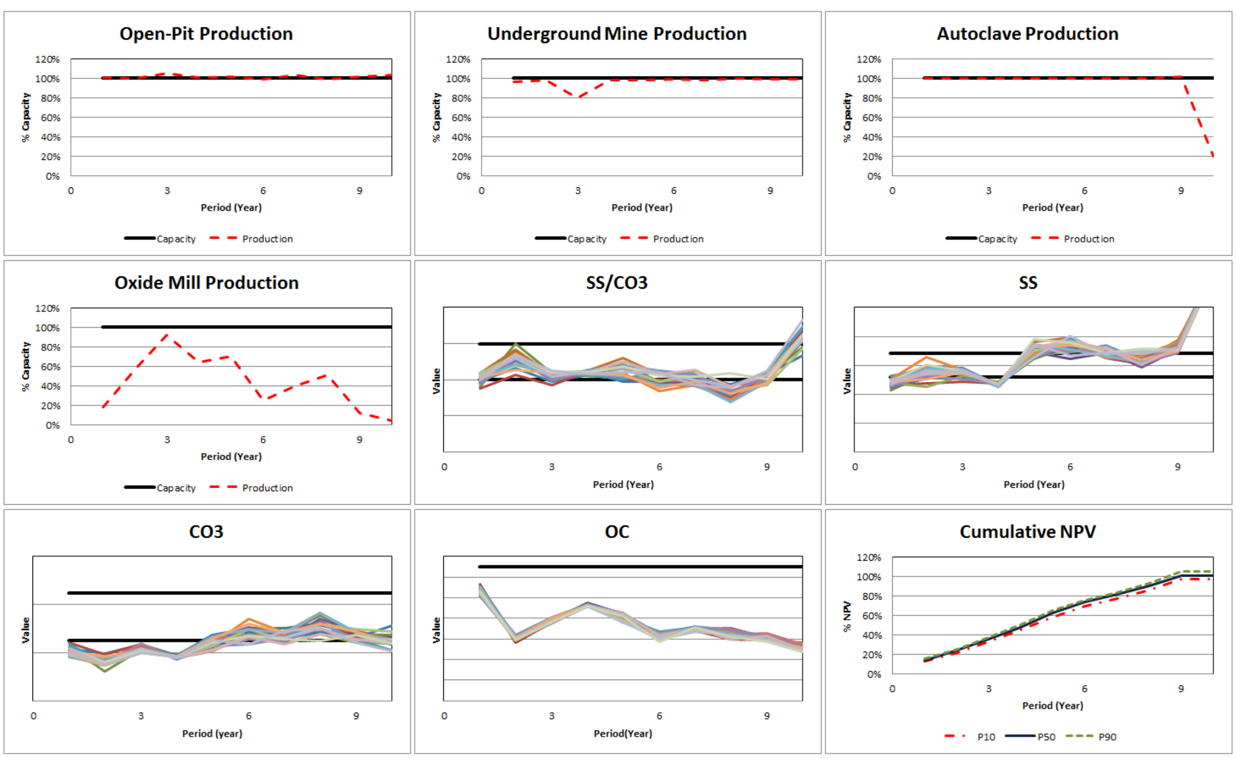


Figure 21: Expected NPVs of stochastic solutions.

The perturbations at operating and transportation decision levels act as a diversification strategy for the unit-based perturbations. Given that in some situations operating modes and transportation systems are not considered, as in the case study, a stand-alone diversification strategy for the unit-based perturbations should be included to better explore the solution domain.

Future extensions of the method may consider stochastic stockpiles, geotechnical and environmental aspects of the underground activities and the optimal consumption rate of external blending material.

Appendix A – Stochastic solution with initial stockpiles



References

Albor, F. and Dimitrakopoulos, R. (2009) Stochastic mine design optimization based on simulated annealing: pit limits, production schedules, multiple orebody scenarios and sensitivity analysis. IMM Transactions, Mining Technology 118(2), A80–A91.

Albor, F. and Dimitrakopoulos, R. (2010) Algorithmic approach to pushback design based on stochastic programming: method, application and comparisons. IMM Transactions, Mining Technology 119(2), A88–A101.

Bodon, P., Fricke, C., Sandeman, T. and Stanford, C. (2010) Combining optimisation and simulation to model a supply chain from pit to port. The Australasian Institute of Mining and Metallurgy, Spectrum Series 17, 277–283.

Chanda, E. (2007) Network linear programming optimisation of an integrated mining and metallurgical complex. In proceedings, Orebody Modeling and Strategic Mine Planning, AusIMM, Spectrum Series 14, 149–155.

Dimitrakopoulos, R. and Ramazan, S. (2004) Uncertainty based production scheduling in open pit mining. SME Transactions 316, 106–112.

Godoy, M. (2003) The effective management of geological risk in long-term production scheduling of open pit mines. PhD Thesis, School of Engineering, University of Queensland, Brisbane, Qld, Australia.

Grieco, N. and Dimitrakopoulos, R. (2007) Managing grade risk in stope design optimisation: probabilistic mathematical programming model and application in sublevel stoping. IMM Transactions, Mining Technology 116(2), 49–57.

Groeneveld, B., Topal, E. and Leenders, B. (2010) A New Methodology for Flexible Mine Design. The Australasian Institute of Mining and Metallurgy, Spectrum Series 17, 113–122.

Hoerger, S., Seymour, F. and Hoffman, L. (1999) Mine Planning at Newmont's Nevada Operations. Mining Engineering 51, 26–30.

IBM, Corp. (2011) IBM ILOG CPLEX Optimization Studio. CPLEX User's Manual 12. IBM Corporation, USA, 1–468.

Kirkpatrick, S., Gelatt, C. D. and Vecchi, M.P. (1983) Optimization by simulated annealing, Science 220, 671–680.

Lamghari, A. and Dimitrakopoulos, R. (2012) A diversified Tabu search approach for the open-pit mine production scheduling problem with metal uncertainty. European Journal of Operational Research 222(3), 642–652.

Lamghari, A., Dimitrakopoulos, R. and Ferland, J.A. (2013) A variable neighbourhood descent algorithm for the open-pit mine production scheduling problem with metal uncertainty, Journal of the Operational Research Society, 1–10.

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.

Menabde, M., Froyland, G., Stone, P. and Yeates, G. (2007) Mining schedule optimisation for conditionally simulated orebodies. In proceedings, Orebody Modeling and Strategic Mine Planning, AusIMM, Spectrum Series 14, 379–384.

Metropolis, N., Rosenbluth, A., Rosenbluth, N., Teller, A. and Teller, E. (1953) Equation of state calculations by fast computing machines. The Journal of Chemical Physics 21, 1087–1092.

Rocchi, L., Carter, P. and Stone, P. (2011) Sequence optimization in longwall coal mining. Journal of Mining Science 47(2), 151–157.

Stone, P., Froyland, G., Menabde, M., Law, B., Pasyar, R. and Monkhouse, P. (2007) Blasor - Blended Iron Ore Mine Planning Optimisation at Yandi, Western Australia. In proceedings, Orebody Modeling and Strategic Mine Planning, AusIMM, Spectrum Series 14, 133–136.

Whittle, G. (2007) Global asset optimization. In proceedings, Orebody Modeling and Strategic Mine Planning, AusIMM, Spectrum Series 14, 331–336.

Whittle, J. (2010) The Global Optimizer Works – What Next? The Australasian Institute of Mining and Metallurgy, Spectrum Series 17, 3–5.

Wooller, R. (2007) Optimising Multiple Operating Policies for Exploiting Complex Resources – An Overview of the COMET Scheduler. In proceedings, Orebody Modeling and Strategic Mine Planning, AusIMM, Spectrum Series 14, 309–316.

Zuckerberg, M., Stone, P., Pasyar, R. and Mader, E. (2007) Joint Ore Extraction and In-Pit Dumping Optimisation. In proceedings, Orebody Modeling and Strategic Mine Planning, AusIMM, Spectrum Series 14, 137–140.

Zuckerberg, M., Van der Riet, J., Malajczuk, W. and Stone, P. (2011) Optimal life-of-mine scheduling for a bauxite mine. Journal of Mining Science 47(2), 158–165.