Les Cahiers du GERAD ISSN: 0711–2440

Adaptive simultaneous stochastic optimization of mining complexes: Where is the value coming from?

M. F. Del Castillo, R. Dimitrakopoulos

G–2021–42

July 2021

La publication de ces rapports de recherche est rendue possible grâce au soutien de HEC Montréal, Polytechnique Montréal, Université McGill, Université du Québec à Montréal, ainsi que du Fonds de recherche du Québec – Nature et technologies.

Dépôt légal – Bibliothèque et Archives nationales du Québec, 2021
– Bibliothèque et Archives Canada, 2021

The publication of these research reports is made possible thanks to the support of HEC Montréal, Polytechnique Montréal, McGill University, Université du Québec à Montréal, as well as the Fonds de recherche du Québec – Nature et technologies.

Legal deposit – Bibliothèque et Archives nationales du Québec, 2021
– Library and Archives Canada, 2021

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

Adaptive simultaneous stochastic optimization of mining complexes: Where is the value coming from?

Maria Fernanda Del Castillo [a, b, c]

Roussos Dimitrakopoulos [a, b, c]

[a] *GERAD, Montréal (Qc), Canada, H3T 1J*

[b] *COSMO – Stochastic Mine Planning Laboratory, Montréal (Qc), Canada, H3A 0E8*

[c] *Department of Mining and Materials Engineering, McGill University, Montréal (Qc), Canada, H3A 0E8*

maria.delcastillo@mail.mcgill.ca
roussos.dimitrakopoulos@mcgill.ca

July 2021
Les Cahiers du GERAD
G–2021–42

Abstract : This paper aims to identify the sources of value created in the strategic plan of a mining complex when the adaptive simultaneous stochastic optimization of mining complex (ASSOMC) approach is used. This approach considers operational and investment alternatives dynamically within the simultaneous stochastic optimization of mining complex (SSOMC) framework, providing an adaptive strategic plan that manages technical risk and maximizes value. A case study on a world-class mining complex illustrates the effects of this optimization model, comparing the adaptive alternatives of the ASSOMC with the fixed SSOMC case. Results show that considering the SSOMC without alternatives as a starting point, including either investment or operational alternatives in a fixed manner, provides an increase in NPV of 4.4% and 2.8%, respectively; whereas considering both jointly increases the NPV by 10.3%. On the other hand, when adaptive changes are considered over investments, such as additional crushers or conveyor belts, the NPV increases further, by about 20%. The focus is placed on identifying the location and components where this extra value is created within the mining complex, understanding the effect that the alternatives have, and capitalizing from them. This study finds that, due to the non-linear synergies that exist between the different components of a mining complex, the adaptive aspect of the approach allows the production plan optimization to be proactive and to tailor its configuration according to possible changes and future developments.

Keywords: Mining complex, stochastic simultaneous optimization, stochastic simulation

1 Introduction

Optimizing the strategic production plan of a mining complex while accounting for uncertainty has proven to maximize value and reduce risk related to production targets (Montiel and Dimitrakopoulos, 2015, 2018; Goodfellow and Dimitrakopoulos, 2016, 2017; Saliba and Dimitrakopoulos, 2018, 2020; Kumar and Dimitrakopoulos, 2019; Levinson and Dimitrakopoulos, 2020). Including flexibility in this strategic plan through investment and operating mode alternatives has been shown to increase the value even further (Montiel and Dimitrakopoulos, 2015; Del Castillo and Dimitrakopoulos, 2019). This study aims to analyze how the adaptive framework proposed by Del Castillo and Dimitrakopoulos (2019) maximizes value by including adaptive alternatives within the strategic optimization of a mining complex. Particularly, it identifies where the extra value being created lies within its components. This is done by understanding the underlying interactions that exist between the alternatives and the components of the mining complex, and capitalizing on them.

Mining complexes consist of interconnected components that transform mined materials into one or more sellable products. Materials are supplied from a set of mines and then transported to different destinations according to their characteristics. These destinations involve either (i) waste dumps if the material is not valuable, (ii) stockpiles for temporary storage, or (iii) further processing streams where the mined materials are transformed into final sellable products. Accounting for the complete mining complex simultaneously to optimize the strategic plan allows taking advantage of the synergies that exist between its components (Hoerger et al., 1999; Stone et al., 2005; Whittle, 2007, 2014, 2018; Pimentel et al., 2010; Goodfellow and Dimitrakopoulos, 2015, 2017; Montiel and Dimitrakopoulos, 2015; Bodon et al., 2018).

The framework referred to as simultaneous stochastic optimization of mining complexes (SSOMC) is based on two-stage stochastic integer programming (SIP) and generates mining complex production schedules that account for the material supply uncertainty governing it (Montiel and Dimitrakopoulos, 2015; Goodfellow and Dimitrakopoulos, 2017). This SSOMC provides a strategic production schedule that defines (i) what material to extract every year from each of the mines involved, (ii) where to send it, and (iii) how to process it. Material supply uncertainty is considered the major contributor to not meeting production targets, and arises because the relevant information regarding metals and material characteristics is obtained from a limited number of available drill holes (Ravenscroft, 1992; Dowd, 1994, 1997; Dimitrakopoulos et al., 2002; Godoy, 2003). This uncertainty is addressed in the context of geostatistical simulations (Goovaerts, 1997; Remy et al., 2009; Gómez-Hernández and Srivastava, 2021), where a set of equally probable mineral deposit simulations is used to quantify uncertainty while representing the local variability of the attributes of interest.

Traditionally, strategic mine production schedules consist of a fixed, unique plan and do not consider possible changes that may occur during their expected production life. Instead, a complete re-optimization is performed on a yearly basis. However, these reactive modifications can be shortsighted and may result in suboptimal mine plans, as their timing and design are not in line with the original plan (Siegel et al., 1987). As a result, it has been shown that there is considerable value gained from accounting for possible alternatives in production plans from an early stage of the optimization and not as the aftermath of production outcomes (Cardin et al., 2007; Goodfellow, 2014; Hu and Cardin, 2015; Montiel and Dimitrakopoulos, 2015; Del Castillo and Dimitrakopoulos, 2019). For example, investments in capital expenditures (CAPEX) such as a new processing plant or a crusher require years of planning for budget approvals, installation, connections to the existing system, and so on. Thus, it is beneficial to know in advance that these investments may happen and when, before they become imminent and delays in their construction result in a loss of value.

Del Castillo and Dimitrakopoulos (2019) extend the SSOMC model into an adaptive framework with representative branching, referred to as the adaptive model (ASSOMC). The representative branching allows the optimization process to dynamically branch the mining complex design in future years if there is a representative probability of investing in a large CAPEX alternative, which is not certain at present. Branching the production plan is allowed for only a subset of feasible alternatives, referred to as "branching alternatives", which depend on the mining complex's characteristics and correspond to investments that would significantly impact the mining complex configuration and schedule. The ASSOMC formulation includes dynamic decisions over CAPEX alternatives and operating modes (Del Castillo, 2018), allowing the model to adapt the strategic plan in later periods. Operating-mode alternatives define different possible configurations at which the mining complex's components can operate according to the material and conditions being dealt with (Montiel and Dimitrakopoulos, 2015). Due to the synergies that exist between the different components of a mining complex and the alternatives available, these configurations may have significant effects on other components down the processing stream. For example, at the mine level, a denser blasting pattern might help the crushers pass more mined material, increasing the feeding of the mills at a processing level. Ultimately, operating mode alternatives enable a better representation of the actual performance of the different processing streams.

These alternatives create value by providing flexibility to act upon and adapt production plans, allowing the mining complex to prepare if future information suggests the current mining complex plan should be substantially changed. However, several alternatives can arise in large mining complexes, both operationally and in terms of capital expenditures. Some of these alternatives involve strategic requirements and must be planned in advance to be available when needed, especially for investments in new infrastructure or specific mining equipment. Different alternatives will entail different requirements, and will have a different impact on value creation. Thus, it is crucial to have an early understanding of which alternatives should be considered and the probability of investing in them in the future. The ASSOMC method provides a dynamic strategic plan for a mining complex that incorporates the probability and timing of different feasible alternatives, offering a global view of the mining complex and possible future developments. The analysis also provides valuable insights towards evaluating how much should be invested in the first place for the chosen alternatives to be available.

This paper studies where the value is being created in the ASSOMC and compares it to the previous SSOMC non-adaptive approach. Different types of alternatives are considered, allowing the model to choose the most valuable ones, and define the optimal timing to implement them. The following section briefly describes the adaptive simultaneous optimization method, explaining its main differences and extensions compared to the stochastic simultaneous optimization model without alternatives presented by Goodfellow and Dimitrakopoulos (2017). Next, a case study at a world-class mining complex is presented, which focuses on identifying the value generated in the strategic plan by considering a set of investment and operating mode alternatives within the optimization in both an adaptive (ASSOMC) and a non-adaptive, fixed manner (SSOMC). Fixed alternatives are analyzed both separately and simultaneously to fully understand their effects on value creation. Results are compared to the adaptive production plan, which allows dynamic changes in the mining complex design in future years. Conclusions follow.

2 Adaptive simultaneous optimization: An overview

ASSOMC (Del Castillo and Dimitrakopoulos, 2019) includes dynamic decisions over CAPEX investments and operating mode alternatives throughout the optimization to have the flexibility to react to possible future changes due to the uncertainty. In this case, the uncertainty considered is in the supply, represented through a set of S geological simulations of the pertinent properties of the mineral deposit involved. The strategic mine production plan is optimized over T years, aiming to maximize the following objective function.

$$max \frac{1}{|S|} \sum_{s \in S} \sum_{t \in T} (\text{Disc. Profit}_{s,t} - \text{Invest. Costs}_{s,t} - \text{Penalty for Deviations}_{s,t}) \tag{1}$$

The first term of Equation (1) corresponds to all discounted revenues from the final products, minus extraction, processing, handling, and transportation costs. The second term considers the purchase costs of the different investments acquired throughout the life of the asset (LOA). Finally, the third term aims at managing risk related to supply uncertainty by minimizing deviations from production targets. These targets consider maximum production and extraction capacities, blending targets, and constraints in the different processing streams of the mining complex.

In this model, non-anticipativity constraints are included to allow the adaptive two-stage optimization model to branch, and at the same time, make decision variables remain constant within a branch (Birge and Louveaux, 1997). These constraints link the separate scenarios and ensure that decisions remain non-anticipative of future information. In this case, these constraints are present for all decisions related to i) extraction sequence, ii) destination policy, iii) operating modes, and iv) CAPEX investments that do not branch (non-branching investments). A representation of the set of non-anticipative constraints related to the extraction sequence decisions ($x_{b,t,s}$) is presented in Equation (2). Variable $x_{b,t,s}$ equals 1 if block b of mine M is extracted in year t, in scenario s, and 0 otherwise. Given that Ω_ρ is the set of scenarios in a branch at a given period, and $\Omega_{\rho 1} \cup \Omega_{\rho 2} = \Omega_\rho$ are scenario partitions, where $\Omega_{\rho 1} = \{s\ ;\ invest = \text{true}, \forall s \in \Omega_\rho\}$, $\Omega_{\rho 2} = \{s\ ;\ invest = \text{false}, \forall s \in \Omega_\rho\}$.

$$(1 - A_{t-1})\,(x_{b,t,s} - x_{b,t,s'}) = 0, \qquad \forall t, t-1 \in T;\ b \in M;\ s \in \Omega_{\rho 1};\ \ s' \in \Omega_{\rho 2} \tag{2}$$

Variable A_{t-1} defines if the design branches and is activated (i.e., equals 1) in period $t-1$ if there is a representative probability (R^*) of investing in an item of branching CAPEX. This activation eliminates constraint (2) and allows decisions to vary for the following planning period (t). However, if A_{t-1} is not activated (equals to 0), constraint 2 enforces all extraction decision variables to be equal throughout all scenarios. Please refer to Del Castillo (2018) for details on the calculation of A_{t-1} and for the full model.

The representative probability R^* corresponds to the probability of acquiring a branching investment. For this, a threshold parameter $R \in [0, 0.5]$ is defined, where branching only occurs when the probability of investing (R^*) falls within this threshold ($R^* \in [R,\ 1-R]$). If the probability of investing is lower than the threshold, the solution does not branch, and no investment is made. On the other hand, if the probability is higher than the threshold, there is also no branching and the whole mine plan is set to invest.

The proposed adaptive two-stage stochastic programming model is solved using a rolling-horizon decision-making mechanism (Sethi and Sorger, 1991; Bertsekas et al., 1997; Adulyasak et al., 2015). It initially solves the simultaneous two-stage SIP model proposed by Goodfellow and Dimitrakopoulos (2016). Then, it iteratively fixes decisions on an increasing time horizon and allows later periods to differ. This process enables quantifying the probabilities of investing. If these probabilities are representative, the model branches the design and rolls back to generate feasible strategic plans for each branch, later fixing the decisions taken until that period. This process is repeated until all mine production periods of the mining complex are fixed. The described mechanism creates value by allowing the schedule to vary given the uncertainties present in later production periods, and more importantly, by optimizing all the mining complex's i) scheduling, ii) destination, iii) processing, iv) investment, and v) operational decisions simultaneously.

3 Case study

The case study presented herein consists of one of the largest copper-producing mining complexes in the world, as illustrated in Figure 1. This mining complex consists of two mines, referred to as Mine 1 and Mine 2 for confidentiality reasons, from where material is simultaneously extracted to be stocked, dumped, or sent through five different crushers to feed: i) three different processing mills that treat high-grade sulphide material, ii) a sulphide leach that treats run of mine low-grade sulphide material, and iii) an oxide leach pad that treats oxides and mixed material. This mining complex has a LOA of over 100 years. In this study, only the initial 20-year LOA plan is optimized. The uncertainty in the supply of material from the two mines is quantified by sets of equally probable geostatistical simulations, generated using the direct block simulation method for multiple correlated variables (Boucher and Dimitrakopoulos, 2009) for copper, molybdenum, iron, and arsenic. Figure 1 also shows the five crushers that are available in the mining complex, which have a critical role in defining how much material is fed to the mills and, thus, how much sellable product is generated.

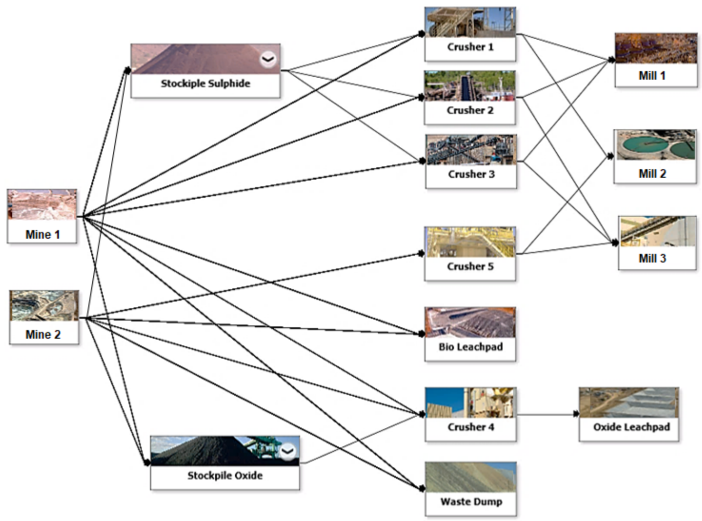


Figure 1: Diagram of the components of the mining complex

Five mine plans are compared. Four of these are generated by different variations of the SSOMC method defined in Goodfellow and Dimitrakopoulos (2016), and the fifth, by the ASSOMC model detailed in Del Castillo and Dimitrakopoulos (2019). More specifically, the five cases considered are:

1. Base Case: SSOMC without alternatives.
2. OpModes Case: Same as the Base Case in (1) but including the optimization of operating mode alternatives. In this case, the operating modes considered are: i) adapting the blasting pattern to aid fragmentation in both the mines of the mining complex, and ii) adapting the throughput-recovery relation at the three different plants, according to the amount and quality of material fed that year. Details of each operating mode are given in Table 1.
3. CAPEX Case: Same as the Base Case in (1) but including the optimization of investment alternatives over the LOA. These investments are presented in Figure 2, with their respective operational and economic details given in Table 1.
4. Combined Case: Same as the Base Case in (1) but including the simultaneous optimization of both sets of alternatives: operating modes as in (2) and the capital expenditure investment defined in (3) over the LOA.
5. Adaptive Case: Adaptive two-stage SIP model with representative branching (ASSOMC). Same as the Combined Case in (4) but including the alternative of dynamically branching the mining complex design over large investments (identified as "once/LOA" in Table 2).

Table 1: Definition of operating mode alternatives considered

Mine Blasting Modes		Mill's Operating Modes	
Attribute affected	**Amount**	**Attribute affected**	**Amount**
Blasting cost at mine j	15%	Recovery at plant j	0.9%
Crushing capacity at crusher c	7%	Throughput at plant j	−12%

Table 2: Definition of investment alternatives considered

	Trucks/ mine	Shovels/ mine	Secondary Crusher at Mill 3	Additional Crusher at Mine 1	Conveyor Belt C5-Mill1
Undisc. cost	MUS$4.8	MUS$32.0	MUS$45.0	MUS$400.0	MUS$50.0
Life of equip.	7 years	7 years	25 years	25 years	25 years
Periodicity	2 years	2 years	once / LOA*	once / LOA*	once / LOA*
Lead time	1 year	1 year	3 years	3 years	2 years
Max. purchase	100 u.	15 u.	1 unit	1 unit	1 unit
Initial capacity	100 / 40 u.	14 / 6 u.	-	-	-
Ton. increment	2.9 Mt/u.	20.3 Mt/u.	5.0 Mt/unit	54.0 Mt/unit	Connection
	(Non-branching investments)		*(*Branching investments)*		

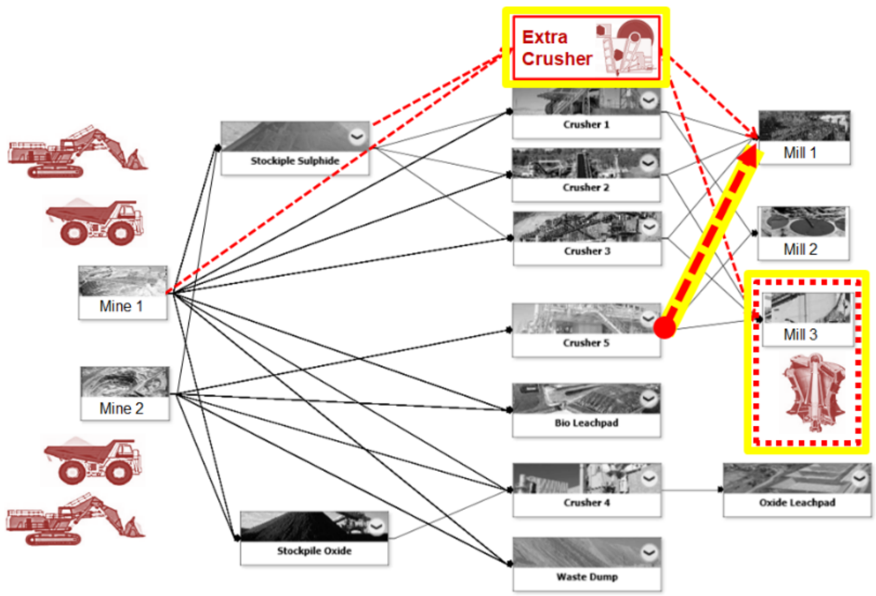


Figure 2: Exact location of CAPEX alternatives considered (in red), highlighting the three branching alternatives (in yellow)

As cases (1) and (2) do not optimize investment decisions, it is assumed that they consider a constant truck and shovel fleet of size equal to the initial capacity presented in Table 2. Thus, purchase costs are automatically incurred to replace them at the end of the equipment life. In the OpMode Case (2), the first alternative specifies that a denser blasting pattern increases the amount of material passing through the crushers. This will consequently increase the feed at the mill, allowing the mining complex to process more material if there is spare capacity.

Cases (1)–(4) will be referred to as “Static Cases” and will be analyzed together to evaluate the individual value contribution of each type of alternative (investments and operating modes). Finally, the Combined Case (4) will be compared to the Adaptive model (5).

3.1 Performance of Static Cases

Figure 3 presents the net present value (NPV) of each of the four static cases. All cases are compared to the Base Case’s NPV (defined as 100%). By considering the operating mode alternatives described in Table 1 exclusively, the NPV increases by 2.8% (OpMode Case). In the case of the CAPEX alternatives shown in Table 2, the NPV increases by 4.4%. Here, the optimization process does not invest in either the conveyor belt or the secondary crusher that would increase the processing capacity of Mill 3; instead it invests in the additional crusher alternative in year 4. However, when both sets of alternatives are considered simultaneously in the Combined Case, the added value reaches 10.3%, which is considerably higher than the addition of both individual contributions. Details of the results obtained in the Combined Case are presented in the following section.

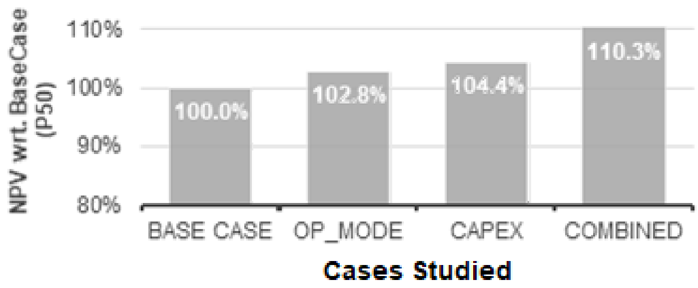


Figure 3: NPV of all cases considered, relative to the Base Case's NPV (set as 100%)

The results show the non-linear synergies that exist between the mining complex components and the different alternatives considered. These synergies are highlighted in Figure 4, which shows in further detail the relation and dependency of both investment and operational alternatives within the mining complex, thus emphasizing how one decision will inevitably alter the others downstream.

The interaction of the alternatives and their effect on the mining complex's NPV can be further explained by analyzing some processing streams more closely. Figure 5 presents the risk profiles of the material feed for one of the three sulphide mills (Mill 3), compared to the processing capacity available (set as 100%). In the figure, the dashed, full, and dotted black curves represent the 10^{th}, 50^{th}, and 90^{th} percentiles of material fed. These percentiles correspond to a 10%, 50%, and 90% probability of the feed being under the curves represented in the figure, respectively. Additionally, Figure 5 presents the operating mode capacity each year (in a dashed red line when available), showing when the optimizer chooses to reduce the throughput to increase recovery, as defined by the operating mode's configuration.

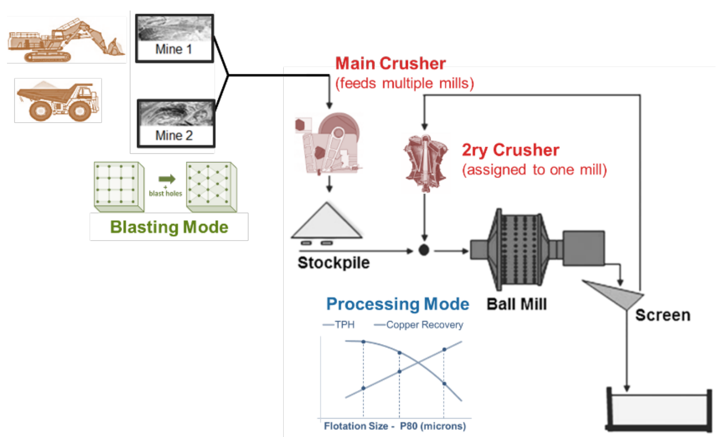
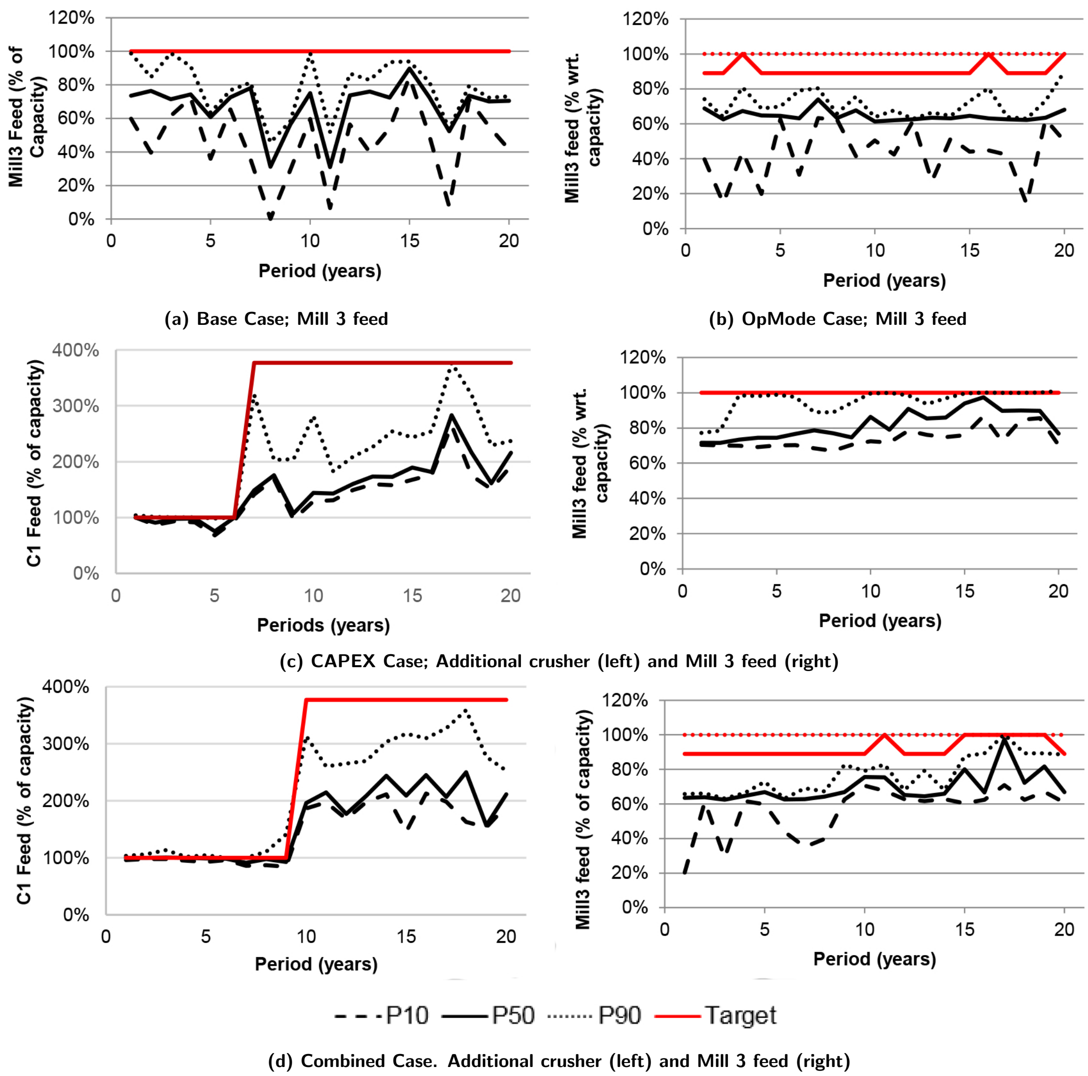


Figure 4: Example of the interdependencies between the different investment and operational alternatives along the processing stream.

Figure 5a corresponds to the Base Case feed of Mill 3. The figure shows there is a spare processing capacity of around 20% in several years. Figure 5b corresponds to the OpMode Case, where the optimizer can choose to reduce the throughput every year in order to increase metal recovery. The figure shows that this option is selected for most years, which is consistent with graph (a), where part of the mill capacity was left unused. Thus, the optimization process chooses to increase metal recovery, and, therefore, cash flow, and reduce the throughput, taking advantage of the available capacity in combination with the possible supply of material mined in the corresponding year.

Figure 5c presents the CAPEX Case. Here, the only large investment that takes place is the additional crusher in year 4 (Figure 5c-left), allowing for the feed of more material starting from year 7. The right side of Figure 5c presents the resulting mill feed with the additional crusher available. Compared to the Base Case (a), the optimization process can better decide how and where to process the extracted material, taking advantage of the mill's capacity and achieving a more stable mill feed. Finally, Figure 5d illustrates the results of the Combined Case. Here, the optimization process does not invest in a secondary crusher; however, it invests in a conveyor belt in year 5 and an additional crusher in year 7, three years later than the CAPEX Case. In the Combined Case, the optimization process decides what material to extract, where and how to process it, initially benefiting from adapting the throughput-recovery operating mode during years of reduced feed. Thus, the investment in an additional crusher can be delayed, discounting its cost while obtaining a stable mill feed.



(a) Base Case; Mill 3 feed

(b) OpMode Case; Mill 3 feed

(c) CAPEX Case; Additional crusher (left) and Mill 3 feed (right)

(d) Combined Case. Additional crusher (left) and Mill 3 feed (right)

Figure 5: Mill 3's processing stream performance for each static case studied

It should be noted that each case presented corresponds to physically different production schedules. Fore these schedules, the optimization process considers the mining complex configuration and the available alternatives, as well as the quantified uncertainty in the grades and material types of the simulated deposit models, to define what material is mined when, as well as where and how it is processed. This example highlights how additional alternatives allow the optimizer to improve the performance of the different mining complex components and results in a production schedule that increases profit. Figure 6 shows the distribution of value generated within the mining complex for the Base Case (left) and the Combined Case (right).

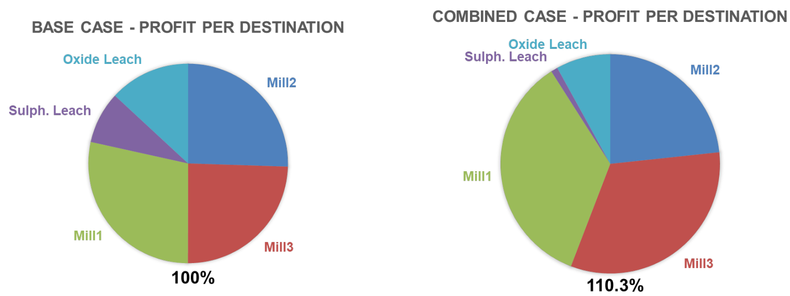


Figure 6: Profit per processing stream for the Base Case (left) and the Combined Case (right)

As presented in Figure 3, the Combined Case generates a 10.3% higher NPV than the Base Case, with most of this value being created at the mills. The most significant difference between both cases is seen in Mill 1. This processing plant receives up to 25% of its annual feed from Mine 2 thanks to the conveyor belt investment, which allows the connection between Mine 2 and Mill 1. Additionally, both Mills 1 and 3 start receiving more material due to the added crusher, which increases the amount of rock fed from Mine 1. Finally, all three mills also benefit from the operating modes, which allows for maximizing recovery or throughput according to the material scheduled to be mined each year. In this case, no alternatives affect the leach pads, which might be why there is such a low cash flow contribution coming from them. In addition, material that was initially sent to the sulphide leach in the Base Case might be sent to the mills in the Combined Case due to the increased crushing capacity. On the other hand, oxide material can only be processed in the oxide leach; as no operating mode is applied in this component, there is no difference seen between these cases.

3.1.1 Performance of Combined vs Adaptive Case

The previous section showed that including both investment and operating mode alternatives simultaneously in the optimization provides additional value due to non-linear relations existing along the different mining complex components. The next step aims to identify the importance of considering some of these alternatives dynamically. Thus, the Combined and the Adaptive cases are compared.

Figure 7 presents the fleet acquisition plan of Mine 1 and Mine 2 for the Combined Case. The columns show the equipment purchases for each mine, and the lines indicate the respective capacity and actual extraction for the 20 years of optimized production. In this case, the optimization process decides to purchase considerably less equipment than the assumed Base Case's fleet size (available over the first two years) and only increases it after year 10. Assuming that this capacity is not needed, delaying investments is beneficial in terms of maximizing NPV.

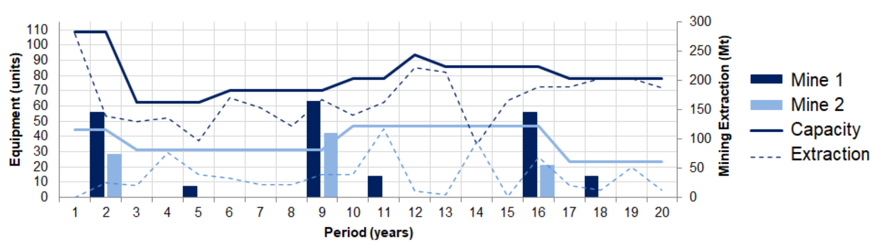


Figure 7: Fleet acquisition plan for Mine 1 and Mine 2 for the Combined Case

Figure 8 presents the annual feed of each mill's material for the 10th, 50th, and 90th percentiles considering the grade and material type uncertainty in the deposit for the production schedule of the Combined Case. Additionally, the figure shows the operating mode capacity in each year ("OM capacity"), showing that, according to the extraction schedule defined, the optimizer reduces the throughput to increase recovery in several years, especially during the first years. Consistent with the decision to delay costly investments to increase extraction capacity, the optimization process can take advantage of extra revenue due to an increased metallurgical recovery at the mills when the feed is reduced. This reduction may be caused by less material being extracted during year of the defined extraction sequence or by the destination policy's decisions to send material to different processing streams. The rightmost diagram of Figure 8 also shows the amount of material being fed from Mine 2, thanks to the conveyor belt investment in year 5, which connects crusher 5 with Mill 1.

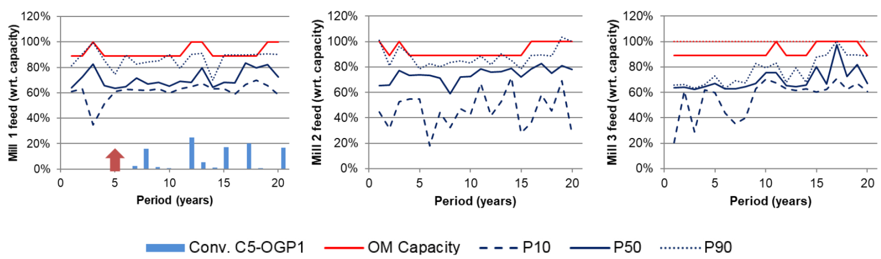


Figure 8: Annual feed of each mill for the 10th, 50th, and 90th percentiles of the Combined Case

On the other hand, the Adaptive Case is obtained by solving the ASSOMC, allowing the optimizer to branch the design over the branching investments identified in Table 2. As explained in Section 2, this optimization provides a mining complex design tree that presents the feasible representative mining complex designs with i) their investment timings, ii) corresponding production plans, and iii) probabilities of occurrence. The resulting tree is presented in Figure 9, where four final branches are defined.

The first four years of production are the same as the initial four years of the Combined Case. The first branching occurs at year 5, where there is a 40% chance of investing both in the additional crusher and the conveyor belt connecting crusher 5 with Mill 1. If this happens (top branch), then there is a 42% chance of investing in the secondary crusher in year 12. On the other hand, if there are no investments made in year 5 (bottom branch with 60% chance), then there is an additional crusher investment in year 7, and later a 50% chance of investing in a secondary crusher. It can be noted that, in this case, there is no branching over the decision of investing on the additional crusher, as an 85% chance of investment is considered representative enough to be a scenario-independent decision.

Figure 10 presents a cross-section of the NS direction of the resulting schedule of Mine 1 for the Combined Case. Next, Figure 11 presents cross-sections of the schedules for each of the four branches of the Adaptive Case for Mine 1, on the NS and EW directions, on the same coordinates as Figure 10. As mentioned previously, each branch of the adaptive optimization's solution tree represents a different schedule and production plan for the mining complex. In this plan, the initial years are shared with the ones of the Combined Case schedule that is used as starting point, and some later years may also be shared between branches if there are later investments. For instance, Figure 9 shows that all four branches share their first four years of production schedule from the Combined Case. This can be clearly confirmed with the EW cross-sections of Figure 11. Here, the dark blue color represents the initial years of extraction, which are equivalent in all four cases. Later, branches #1 and #2 share their first 11 years, while branches #3 and #4 share their initial nine years. This can also be seen in Figure 11, where the top two cross sections corresponding to branches #1 and #2 are initially equivalent, extending towards the North. However, later developments of extraction vary significantly, where, for example, branch #1 chooses to extract material towards the East and reaches the bottom of the pit at the NS cross-section earlier, as compared to branch #2. Meanwhile, branch #1 delays the extraction at the bottom of the pit but ends up removing more material in this area towards later periods. Many similar comparisons can be extracted from analyzing Figure 11. For clarification and presentation purposes, just the details of the production plan of Branch #3 are presented, which has one of the highest probabilities of occurring (30%). Here, the optimizer invests in both a secondary and an additional crusher, but not in the conveyor belt.

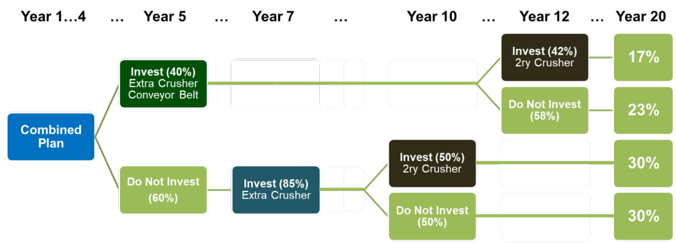


Figure 9: Mining complex design tree obtained by the adaptive optimization, presenting possible mining complex configurations and their probabilities of occurrence

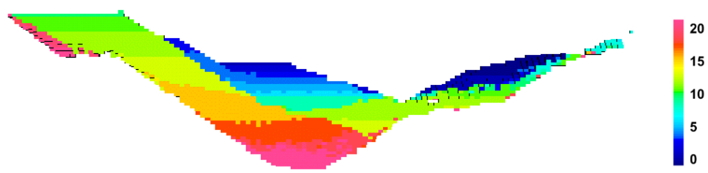


Figure 10: NS Cross-section of the Combined Case schedule for Mine 1

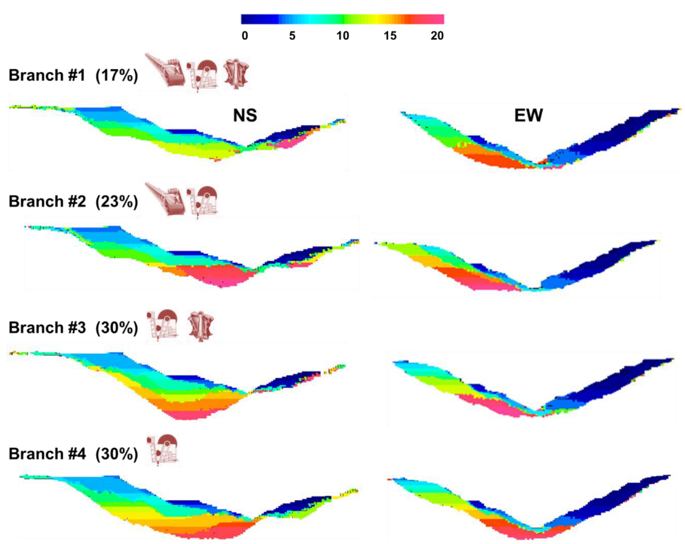


Figure 11: Cross-section of the schedules of the Adaptive Case for Mine 1, for each branch and their corresponding investments (on the NS and EW directions)

Figure 12 shows the extracted material per mine and the number of equipment purchased during the 20 years for this case, and Figure 13 presents the risk profiles of the material fed to the three mills for the same period. As in the Combined Case presented in Figure 7, this production schedule also requires considerably less extraction equipment than the Base Case (equal to the first two years of extraction in all cases). As presented in Figure 9, there is an additional crusher investment at year 7 and a secondary crusher in year 10. Due to lead times, the secondary crusher is operational on year 13, consistent with the increase in processing capacity presented on the right side of Figure 13. This figure also shows a rise in the amount of material being received at the mills towards the last ten years of the production plan, which is made possible by the increased crushing capacity from the additional crusher.

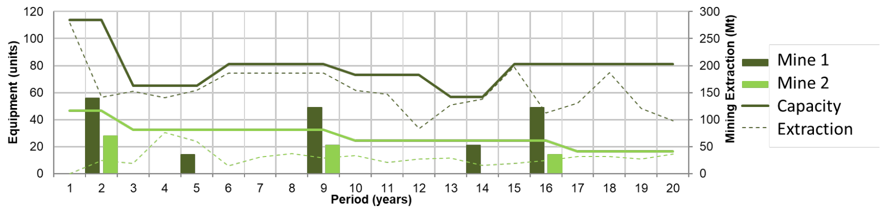


Figure 12: Fleet acquisition plan for Mines 1 and 2 for Branch #3 of the Adaptive Case

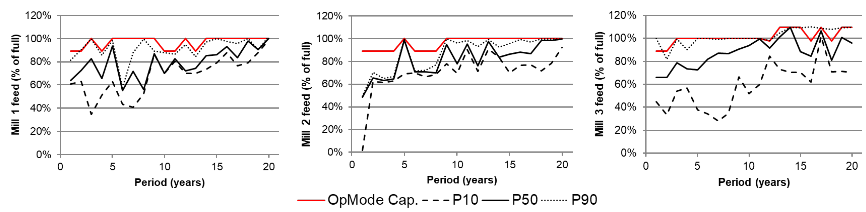
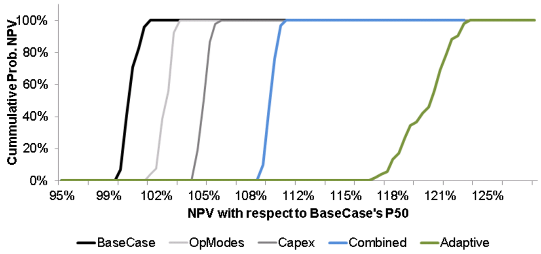


Figure 13: Risk analysis of annual feed of Mills 1, 2, and 3 for Branch #3 of the Adaptive Case

3.2 Discussion of NPV distributions

The left side of Figure 14 shows the NPV distribution for each of the five cases presented: i) Base Case, without alternatives, ii) CAPEX, with only investment alternatives, iii) OpMode, with only operating mode alternatives, iv) Combined, considering both investment and operating mode alternatives simultaneously, and v) Adaptive, allowing the mining complex design to branch and adapt to possible future evolutions of the mining complex. The right side of Figure 14 shows the difference of each case with respect to the 50$^{\text{th}}$ percentile (P50) of the Base Case's NPV. Thus, for example, the 10$^{\text{th}}$ (P10) and 90$^{\text{th}}$ (P90) percentiles of the Base Case present, respectively, a 1.1% decrease and increase in NPV, relative to the 50$^{\text{th}}$ percentile value; this means that there is a 90% chance of having an NPV lower than 101.1% of the P50's value and 10% chance of NPV being lower than 98.9% of the P50 value.

The NPV distribution presented in Figure 14 shows that the stochastic simultaneous optimization of mining complexes is non-linear, as discussed in Figure 3, where accounting for investment and operating mode alternatives simultaneously produces considerably more value than if these alternatives are considered independently. Additionally, Figure 14 shows the substantial increase in NPV of the Adaptive Case, where alternatives are considered dynamically, allowing the mining complex design to adapt and change configuration. This increase in value is possible because the production plan of the mining complex adapts to potential future developments and allows the initial plan to change in response. This analysis also provides more detailed information about the appeal of the different alternatives available. For example, the Combined Case did not consider the investment of a secondary crusher. However, in the solution tree of the Adaptive Case, one can see that there is a 47% chance of this investment being beneficial, meaning that this investment alternative should not be overlooked. In other words, more than an exact financial forecast, the adaptive method provides an informed view of the possible developments of the mining complex, offering flexibility to the production scheduling process and allowing for a more proactive response once more information becomes available.



	Increase wrt. Base Case (%)		
	P10	**P50**	**P90**
Base Case	−1.1	–	1.1
CAPEX	3.0	4.4	6.1
OpMode	2.4	2.8	3.0
Combined	8.9	10.3	11.5
Adaptive	18.6	20.5	22.7

Figure 14: NPV distribution for each case studied (left) and relative increase with respect to the P50 value of the Base Case (right)

4 Conclusions

This study identifies the sources of value in the adaptive simultaneous stochastic optimization of mining complexes (ASSOMC). This adaptive model acknowledges that uncertainty can cause the future developments of the mining complex design to differ from what was initially planned. Thus, it facilitates the transition to possible adaptations, allowing for a more proactive response to change. Additionally, this study highlights the importance of accounting for all decision variables simultaneously, including investment and operating mode alternatives.

A case study at a world-class mining complex is presented to illustrate the effects of considering investment and operating mode alternatives in the SSOMC in both a fixed and an adaptive manner. Results show operational improvements, which directly affect project value. This value creation can be explained by the presence of non-linear synergies between the different components and alternatives in the mining complex. For instance, as presented in Figure 3, considering only CAPEX or only operating mode alternatives increases NPV by 4.4% and 2.8%, respectively. However, accounting for both sets of alternatives jointly increases the NPV by 10.3%, which is considerably higher than the addition of individual contributions. This non-linearity shows that, because of the synergies between the different components and the configurations of a mining complex, it is crucial to optimize all decision variables simultaneously. Such variables include i) the extraction sequence of the related mines, ii) the destination policy of the extracted material, iii) processing stream decisions, iv) the operational modes of these mines and processing streams and v) the different investment decision alternatives. Additionally, the study concludes that incorporating adaptive changes into the mining complex design in terms of large investments can increase the value even further, between 18% and 22%, which allows the mining complex to react and adapt its configuration according to potential future developments.

References

Adulyasak, Y., Cordeau, J.-F., and Jans, R., 2015. Benders decomposition for production routing under demand uncertainty. Oper. Res. 63, 851–867. https://doi.org/10.1287/opre.2015.1401

Bertsekas, D.P., Tsitsiklis, J.N., and Wu, C., 1997. Rollout algorithms for combinatorial optimization. J. Heuristics 3, 245–262.

Birge, J., and Louveaux, F., 1997. Introduction to stochastic programming. Springer-Verlag, New York.

Bodon, P., Fricke, C., Sandeman, T., and Stanford, C., 2018. Combining optimisation and simulation to model a supply chain from pit to port, in: Advances in Applied Strategic Mine Planning. Springer International Publishing, pp. 251–267. https://doi.org/10.1007/978-3-319-69320-0_17

Boucher, A., and Dimitrakopoulos, R., 2009. Block simulation of multiple correlated variables. Mathematical Geosciences, 41, 215–237. doi:10.1007/s.11004-008-9178-0

Cardin, M., Nuttall, W., de Neufville, R., and Dahlgren, J., 2007. Extracting value from uncertainty: A methodology for engineering systems design. INCOSE Int. Symp. 17, 668–682. https://doi.org/10.1002/j.2334-5837.2007.tb02903.x

Del Castillo, F., 2018. Dynamic simultaneous optimization of mineral value chains under resource uncertainty. PhD Thesis. McGill University.

Del Castillo, F., and Dimitrakopoulos, R., 2019. Dynamically optimizing the strategic plan of mining complexes under supply uncertainty. Resour. Policy 60, 83–93. https://doi.org/10.1016/J.RESOURPOL.2018.11.019

Dimitrakopoulos, R., Farrelly, C., and Godoy, M., 2002. Moving forward from traditional optimization: grade uncertainty and risk effects in open-pit design. Min. Technol. 111, 82–88. https://doi.org/10.1179/mnt.2002.111.1.82

Dowd, P., 1997. Risk in minerals projects: analysis, perception and management. Trans. Inst. Min. Metall. Sect. A-Mining Ind. 106, A9–A18.

Dowd, P., 1994. Risk assessment in reserve estimation and open-pit planning. Int. J. Rock Mech. Min. Sci. Geomech. Abstr. 4, 168A.

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

Gómez-Hernández, J.J., and Srivastava, R.M., 2021. One step at a time: the origins of sequential simulation and beyond. Math Geosci 53, 193–209. https://doi.org/10.1007/s11004-021-09926-0

Goodfellow, R., 2014. Unified modelling and simultaneous optimization of open pit mining complexes with supply uncertainty. PhD Thesis. McGill University.

Goodfellow, R., and Dimitrakopoulos, R., 2017. Simultaneous stochastic optimization of mining complexes and mineral value chains. Math. Geosci. 49, 341–360. https://doi.org/10.1007/s11004-017-9680-3

Goodfellow, R., and Dimitrakopoulos, R., 2016. Global optimization of open pit mining complexes with uncertainty. Appl. Soft Comput. 40, 292–304. https://doi.org/10.1016/J.ASOC.2015.11.038

Goodfellow, R., and Dimitrakopoulos, R., 2015. Stochastic optimization of open pit mining complexes with capital expenditures: application at a copper mining complex. In, Bandopadhyay, S, Ed., Proceedings, Application of Computers and Operations Research in the Mineral Industry (APCOM), Society for Mining, Metallurgy & Exploration, pp.657–667

Goovaerts, P., 1997. Geostatistics for natural resources evaluation. Oxford University Press.

Hoerger, S., Seymour, F., and Hoffman, L., 1999. Mine Planning at Newmont's Nevada Operations. Min. Eng. 51, 26–30.

Hu, J., and Cardin, M., 2015. Generating flexibility in the design of engineering systems to enable better sustainability and lifecycle performance. Res. Eng. Des. 26, 121–143. https://doi.org/10.1007/s00163-015-0189-9

Kumar, A., and Dimitrakopoulos, R., 2019. Application of simultaneous stochastic optimization with geometallurgical decisions at a copper–gold mining complex. Min. Technol. 128, 88–105. https://doi.org/10.1080/25726668.2019.1575053

Levinson, Z., and Dimitrakopoulos, R., 2020. Adaptive simultaneous stochastic optimization of a gold mining complex: A case study. J. South. African Inst. Min. Metall. 120. https://doi.org/10.17159/2411

Montiel, L., and Dimitrakopoulos, R., 2018. Simultaneous stochastic optimization of production scheduling at Twin Creeks Mining Complex, Nevada. Min. Eng. 70, 48–56.

Montiel, L., and Dimitrakopoulos, R., 2015. Optimizing mining complexes with multiple processing and transportation alternatives: An uncertainty-based approach. Eur. J. Oper. Res. 247, 166–178. https://doi.org/10.1016/J.EJOR.2015.05.002

Pimentel, B., Mateus, G., and Almeida, F., 2010. Mathematical models for optimizing the global mining supply chain, in: Intelligent Systems in Operations: Methods, Models and Applications in the Supply Chain. Business Science Reference, pp. 133–163.

Ravenscroft, P., 1992. Risk analysis for mine scheduling by conditional simulation. Trans. Inst. Min. Metall. Sect. A. Min. Ind. 101, 104–108.

Remy, N., Boucher, A., and Wu, J., 2009. Applied geostatistics with SGeMS: a user's guide. Cambridge University Press.

Saliba, Z., and Dimitrakopoulos, R., 2020. An application of simultaneous stochastic optimisation of an open-pit mining complex with tailings management. Int. J. Mining, Reclam. Environ. 34, 592–607. https://doi.org/10.1080/17480930.2019.1688954

Saliba, Z., and Dimitrakopoulos, R., 2018. Simultaneous stochastic optimization of an open pit gold mining complex with supply and market uncertainty. Min. Technol. 128, 216–229. https://doi.org/10.1080/25726668.2019.1626169

Sethi, S., and Sorger, G., 1991. A theory of rolling horizon decision making. Ann. Oper. Res. 29, 387–415. https://doi.org/10.1007/BF02283607

Siegel, D., Smith, J., and Paddock, J., 1987. Valuing offshore oil properties with option pricing models. Midl. Corp. Financ. J. 5, 22–30.

Stone, P., Froyland, G., Menabde, M., Law, B., Pasyar, R., and Monkhouse, P., 2005. Blended iron-ore mine planning optimization at Yandi Western Australia. AusIMM Spectr. Ser. 14, 117–120.

Whittle, G., 2007. Global asset optimization. Orebody modelling and strategic mine planning. Aust. Inst. Min. Metall. Spectr. Ser. 14, 331–336.

Whittle, J., 2018. The Global Optimiser Works—What Next?, in: Advances in Applied Strategic Mine Planning. Springer International Publishing, Cham, pp. 31–37. https://doi.org/10.1007/978-3-319-69320-0_3

Whittle, J., 2014. Not for the Faint-Hearted, in: Orebody Modelling and Strategy Mine Planning. The Australian Institute of Mining and Metallurgy, Perth, WA, pp. 3–6.