

**Block sequencing analysis and importance of mining  
recovery and dilution in mine planning**

by

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## **ORIGINALITY STATEMENT**

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A handwritten signature in black ink, appearing to read 'Akseleu', enclosed within a large, irregular, hand-drawn oval shape.

## ABSTRACT

A critical step in open pit mining is determining the appropriate sequence of block extraction, which has a significant impact on mining profitability. The open-pit mining block sequencing issue, which emerges at this stage, is described to find the optimal sequence in which blocks should be extracted following numerous physical and technological restrictions. Moreover, mine planning should take mining recovery and dilution into account and engage fully in planning and optimization processes. The optimal mining block sequencing provides the highest net present value (NPV) of the project. **This paper proposes a mathematical model and software computation for the open-pit mine block sequencing in open pit mining operations. The primary goal was to analyze sequencing, the ultimate pit limit, pushbacks, and scheduling simulation findings, which correspond to real-world mining projects in Datamine Studio NPVS, and compare with optimistic and pessimistic scenarios.** The results showed the highest Net present value is observed in Pit no. 88 in the optimistic scenario (+20% in price) – 914,612,423 \$, while the lowest NPV results were in the pessimistic scenario (-20% in price) - 356,593,171 \$ in Pit no. 82 Moreover, possible optimization improvements of block sequencing, ore recovery and dilution will be addressed. To demonstrate the superior attributes of the enhanced model, an open-pit gold mine case study was presented. The combination of direct block sequencing and the traditional method allows for improving NPV results by 0.43% which is regarded as an achievable outcome. Mine planning software must develop and adapt to meet current requirements and improve innovative solutions to existing block sequencing problems.

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# TABLE OF CONTENTS

TABLE OF CONTENTS.....	5
LIST OF FIGURES.....	7
LIST OF TABLES .....	9
1. INTRODUCTION .....	11
1.1 Background .....	11
1.2 Objectives of the Thesis .....	13
Main Objectives .....	13
1.3 Justification of the R&D.....	13
2. LITERATURE REVIEW .....	14
2.1 BLOCK SEQUENCING .....	14
2.2 MINING RECOVERY AND DILUTION.....	20
2.3 CASE STUDY .....	24
2.3.1 Case study 1 .....	24
2.3.2 Case study 2 .....	27
2.3.3 Case study 3 .....	29
3. METHODOLOGY .....	33
3.1 Justification of selected methods .....	33
3.2 Numerical Model .....	34
3.3 Software computation.....	35
4. RESULTS.....	40

<b>4.1 Base Scenario .....</b>	<b>40</b>
<b>4.2 Optimistic Scenario .....</b>	<b>47</b>
<b>4.3 Pessimistic Scenario .....</b>	<b>52</b>
<b>4.4 Sensitivity Analysis .....</b>	<b>58</b>
<b>4. DISCUSSION .....</b>	<b>60</b>
<b>5. CONCLUSIONS AND RECOMMENDATIONS .....</b>	<b>63</b>
<b>6. REFERENCES .....</b>	<b>64</b>

## LIST OF FIGURES

Figure 1. Two block model (Brickey & Eureka, 2014).....	16
Figure 2. Traditional methodology versus direct block scheduling (P. H. A. Campos et al., 2018). .....	18
Figure 3. Open pit scheme and types of dilution (Ebrahimi, 2013). .....	21
Figure 4. The schematics of the process of Rosebel gold mine complex (LaRoche-Boisvert & Dimitrakopoulos, 2021) .....	25
Figure 5. Stochastic life-of-asset production schedules at the three mines at the RGM mining complex (LaRoche-Boisvert & Dimitrakopoulos, 2021).....	26
Figure 6. Block Schedules for a 7-year period (Saavedra-Rosas, 2016).....	28
Figure 7. A 3D view of the block model (P. Campos et al., 2018). .....	31
Figure 8. Annual scheduling for the red blocks (P. Campos et al., 2018).....	32
Figure 9. Block sequencing by using Direct Block Sequencing (DBS) (P. Campos et al., 2018). .....	33
Figure 10. The graph of Au recovery.....	38
Figure 11. The graph of Cu recovery.....	38
Figure 12. Side view before mining operations.....	40
Figure 13. Side view of pushback no. 1 (Base Case).....	41
Figure 14. Side view of pushback no. 2 (Base Case).....	41
Figure 15. Side view of pushback no. 3 (Base Case).....	42
Figure 16. Side view of pushback 4 (Base Case).....	42
Figure 17. Side view of the pit limit (Base Case).....	43
Figure 18. Plan view of pit limit (Base Case).....	44

Figure 19. The histogram of NPV, ore and waste tonnage (Base Case).....	47
Figure 20. Side view of pushback no. 1 (Optimistic Scenario).....	47
Figure 21. Side view of pushback no. 2 (Optimistic Scenario).....	48
Figure 22. Side view of pushback no. 3 (Optimistic Scenario).....	48
Figure 23. Side view of pit limit (Optimistic Scenario).....	49
Figure 24. Plan view of pit limit (Optimistic Scenario).....	50
Figure 25. The histogram of NPV, ore and waste tonnage (Optimistic Scenario).....	52
Figure 26. Side view of pushback no. 1 (Pessimistic Scenario). ....	53
Figure 27. Side view of pushback no. 2 (Pessimistic Scenario). ....	53
Figure 28. Side view of pushback no. 3 (Pessimistic Scenario). ....	54
Figure 29. Side view of pit limit (Pessimistic Scenario). ....	55
Figure 30. Plan view of pit limit (Pessimistic Scenario). ....	55
Figure 31. The histogram of NPV, ore and waste tonnage (Pessimistic Scenario). ..	57
Figure 32. Graph of NPV vs. Price Sensitivities. ....	58
Figure 33. Graph of revenue vs. Price Sensitivities.....	59
Figure 34. Graph of cut-off grade vs. Price Sensitivities.....	60

## LIST OF TABLES

Table 1. Capacity and Scheduling constraints for developing scheduling (LaRoche-Boisvert & Dimitrakopoulos, 2021) .....	26
Table 2. Main economic and technical parameters (Saavedra-Rosas, 2016). .....	27
Table 3. Production plans for each period (Saavedra-Rosas, 2016). .....	29
Table 4. The strategic planning of the whole project produced the life-of-mine production plan (P. Campos et al., 2018). .....	30
Table 5. Economic parameters of base case (Madani, 2021). .....	36
Table 6. Economic parameters of optimistic scenario (Madani, 2021). .....	36
Table 7. Economic parameters of pessimistic scenario (Madani, 2021). .....	37
Table 8. Recovery formulas (Madani, 2021). .....	37
Table 9. Geotechnical information of block model (Madani, 2021). .....	39
Table 10. Ore, waste, and profit generated within each pushback (Base Case). .....	43
Table 11. Scheduling results of the project (Base Case). .....	44
Table 12. Scheduling results by time periods (Base Case). .....	45
Table 13. LG phases (Base Case). .....	45
Table 14. The cut-off grades of the base case. .....	46
Table 15. Economic output of the simulation (Base Case). .....	46
Table 16. Ore, waste, and profit generated within each pushback (Optimistic Scenario). .....	49
Table 17. Scheduling results by time periods .....	50
Table 18. LG phases (Optimistic Scenario). .....	51

Table 19. The economic cut-off grade of the optimistic scenario.....	51
Table 20. Economic output of the simulation (Optimistic Scenario).....	52
Table 21. The tonnage of ore, waste and profit for each pushback (Pessimistic Scenario).....	54
Table 22. Scheduling results by time periods (Pessimistic Scenario).....	56
Table 23. LG phases (Pessimistic Scenario).....	56
Table 24. The economic cut-off grade of the pessimistic scenario. ....	57
Table 25. Economic output of the simulation (Pessimistic Scenario). ....	57
Table 26. Sensitivity analysis on Net Present Value. ....	58
Table 27. Sensitivity analysis on revenue.....	59
Table 28. Sensitivity analysis on cut-off grade. ....	59

# 1. INTRODUCTION

## 1.1 Background

The most widespread and oldest way of extracting rich material from the earth is open-pit mining. Numerous researchers have been drawn to the operation to explore different areas such as production planning, truck-shovel allocations, risk analysis, and grade mixing. Numerous heuristic, meta-heuristic, and mathematical programming approaches have been used to enhance the functioning of these operations. Their objectives are to maximize profit, decrease expenses, and optimize resource usage or the mining operation's result. Additionally, the mine planning issue has been investigated throughout a variety of periods. Typically, long-term to short-term plans are developed based on varying degrees of detail. Long-term plans often address bigger units of production and determine when and where to extract materials. On the other side, short-term plans focus on smaller units and make more precise choices on production levels, blending, and truck-shovel allocations.

The former - strategic mine planning, starts with the development of a discretized mathematical model of the ore body, referred to as a block model. Typically, a deposit of interest is split into thousands of three-dimensional (3D) rectangular cubes, referred to as a block model. The coordinates of a block show easting (x), northing (y), and elevation (z) of the block (Mousavi et al., 2016). Each block is allocated several geological properties based on data gathered from exploratory drill holes. These attributes include ore and waste grades, rock types, and rock densities. Then, each block within the block model is assigned to a particular order, which is called block sequencing. The block sequencing problem is described as identifying the appropriate sequence for extracting blocks under a variety of practical and technological limitations. Several restrictions are considered in the block sequencing problem, including precedence relations, equipment limits, mineral processing capacity, and grade control. For various time horizons, the block sequencing issue may be addressed. Mousavi et al. (2016) claim that the mine block sequencing issue may be characterized as determining the order in which blocks should be extracted from the mine and assigned to their proper

destinations. Generally, the mine block sequencing model is composed of the following components: blocks, processing circuits, stockpiles, excavators, time horizons, and mining regulations. Apart from which blocks will be mined and when they will be extracted, strategic mine planning deals with where they will be extracted. Destinations represent not only physical locations but also block processing and treatment options. Mills, trash dumps, leach pads, and stockpiles are all examples of block destinations.

The open pit mining block sequencing issue, which emerges at this stage, is specified to establish the optimal sequence in which blocks should be removed according to the various physical and technical restrictions. Another crucial aspect of block sequencing is the determination of the optimal cut-off grade for the mining blocks. The cut-off grade has a direct impact on the economic viability of mining operations for the course of the project's life. The approach of using a high cutoff grade to get a greater overall NPV for a specific project begins with a high cutoff grade. Increased cutoff grade results in greater average grades per ton of ore throughout the earliest stages of the mining sequence; accordingly, higher average grades are realized based on the deposit's grade distribution (Moosavi & Gholamnejad, 2016). The cutoff grade indicates the amount mined, processed, and lastly, the product generated in the refinery for selling in each mining sequence. The success of the project highly depends on the cutoff grade established. As a result, optimizing the cutoff grade is critical in terms of mine life.

Block sequencing is difficult due to the generally large number of blocks, as well as the number of periods, limitations, and inherent complexity. Even though appropriate block sequencing may increase the economic worth of the project, there are also some problems to consider while planning the open pit mine. During extraction, processing, and other mining activities some uncertainties may appear through mining recovery and dilution. Dilution raises the mill's operating costs by increasing the amount of material that must be milled. Apart from its direct effect on a mine's short-term revenue, dilution results in major changes in other aspects, lowering the project's total worth in the long term. Another aspect to mention is the mining recovery of the project. The primary elements affecting the ore recovery ratio include

mining technique, blasting, seismic events, rock bursts, grade control, geology, and other factors such as rock drilling and rock support.

## **1.2 Objectives of the Thesis**

### ***Main Objectives***

There is a great impact of block sequencing on both the mine production aspect and the economic aspect as well. Thus, it is important to sequence blocks in the correct way to maximize the Net Present Value (NPV) of the project. The thesis paper presents an analysis of block sequencing approaches of open pit mines worldwide and suggests possible improvements in the block sequencing model by providing software and design optimization. The software simulation was also produced to represent the block sequencing in open pit mine, which correspond to real-world mining projects. The software algorithm simultaneously produces optimal cut-off grade strategies, sequence of extraction, and scheduling of the project. The main objective was to evaluate and compare three scenarios (base, optimistic, and pessimistic) of the project considering price and mining/processing costs changes. In the discussion section, these outcomes of the software will be evaluated using approaches of other open pit mines.

## **1.3 Justification of the R&D**

This is a significant and complex topic with a multidisciplinary approach that may need evaluation of economic, statistical, and optimization factors concurrently. Economic scheduling directly reflects consideration of time-value-of-money impacts. As technologies developing throughout the years, it is important to implement an appropriate sequencing and scheduling methods.

## 2. LITERATURE REVIEW

### 2.1 BLOCK SEQUENCING

Numerous scientific papers provide distinct optimization approaches in mining block sequencing model problems. As was mentioned before, the mine block sequencing problem is defined as determining the sequence in which blocks should be extracted to minimize stockpiling costs, including rehandling and holding costs, and to satisfy all physical and strategic constraints, including precedence relationships, mining capacity, processing demands, and grade requirements. Additionally, the mine block sequencing solution should optimize material movement from the mine to the processes and stockpiles, as well as from the stockpiles to the processes. However, before extracting mining blocks, ore and waste materials should be determined. To differentiate ore and waste blocks we use a given equation:

$$\text{Economic Block Value} = \text{Revenue} - \text{Mining Cost} - \text{Processing Cost} \quad (1)$$

If the difference between the revenue and the operational cost is negative, we classify the block as waste and compute its extraction cost as simply the product of the amount of waste and the associated mining cost. Otherwise, the block qualifies as an ore block. Based on this classification, we categorize each ore block as destined for the processing plant and each waste block as destined for the dump. From that, we define a new term – cut-off grade for the open pit. A cut-off grade is used to represent the difference between ore and waste in a certain mineral deposit. In general, cut-off grade refers to the minimal quantity of valuable minerals that must occur in a unit of material (e.g., one tone) before it is transported to the processing facility (Mousavi et al., 2014). The cut-off grade of the open pit significantly affects the mine sequences. Moosavi and Gholamnejad (2016) assume that cutoff grade optimization is a multidisciplinary process that considers metal prices, mining costs, milling costs, the processing plant's capacity, mining capacity within the mining operation, mining sequence, deposit grade

distribution, and consequent cash flow. Moreover. The authors claim that maximum present value and constant cut-off grades are incompatible and as a result, numerous attempts have been made to develop a computerized procedure for optimizing cutoff grade while taking mining sequence into account, including utilizing Penalization, Lagrangian relaxation, 4D-Network relaxation, Dynamic programming, and Genetic algorithm.

There are two primary strategies for completing block sequencing. The first is based on the Lerchs-Grossmann algorithm's (LG) production of Nested Pits. This technique utilizes a revenue component to control the size of the pits by discounting the price in the block valuation, followed by various scheduling algorithms. Due to the difficulty of solving the overall open pit planning problem in a single step, the traditional planning process (used by the industry since the 1960s) divides the main problem into several sub-problems, such as determining the ultimate pit limit, generating pushback, scheduling, blending, and optimizing the cut-off grade. Over time, strategies for optimizing these individual options have been developed. For example, Lerchs and Grossmann (1965) developed an algorithm that ensures optimality when determining pit limits to maximize undiscounted cash flow. Additionally, they proposed a way of constructing nested pits to generate pushbacks (P. Campos et al., 2018). However, P. Campos et al. (2018) adds that this approach has three shortcomings: (1) it uses a fixed cut-off grade that is dependent on an arbitrary delineation between waste and ore; (2) it employs stochastic prices to determine the nested pits; and (3) it applies the piecemeal approach to the entire optimization problem, omitting the temporal interaction of resource requirements. Since the extraction sequence is determined, this sequence might stay unchanging for many years. Johnson et al. (2011) agree that commodity prices are unknown, and the company must determine in real time whether the ore grade is high enough to justify further processing in preparation for sale or to simply waste the block.

There are several approaches to optimize block model sequencing. They could be categorized as software optimization and design in a model of the block sequence. According to Brickey and Eurek (2014), most commercial solvers, such as CPLEX (IBM 2011), solve integer algorithms using the branch-and-bound (B&B) technique. Our solution approaches are

aimed to improve the solver's functionality by using the open pit block sequence problem's unique structure. The author provides the following solution methodologies attempt to reduce the solution time for instances of (CPIT) by (1) tightening the formulation; (2) solving the linear programming (LP) relaxation of the integer program at the root node with the proper algorithm and corresponding algorithmic settings; (3) reducing the problem size through variable elimination; and (4) providing the optimizer with an initial integer feasible solution. The first could be enhanced by tightening the restriction set and substituting a collection of variables indicating the period before which a given block must be mined for the set of decision variables determining when a specific block must be mined. In the second case a CPLEX software, for example, has a network simplex method that can solve the LP more quickly when a large component of the constraint matrix of the LP contains a network structure. The third solution provides a variable elimination approach. The author finds that the variables  $y_{bt}$  indicate whether block b should be extracted at period t. Periods t' signify that the variable  $y_{bt'}$  must have the value 0 in any conceivable solution, enabling us to therefore exclude  $y_{bt'}$  from the formulation.

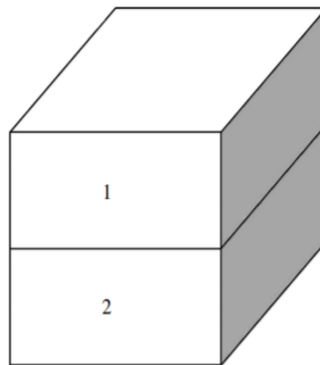


Figure 1. Two block model (Brickey & Eurek, 2014).

Figure 1 illustrates a simple 2 block model. Because block 1 must be mined prior to block 2, it is mathematically impossible (i.e., practically impossible) to extract block 2 during

period 1. As a result, the value of the variable  $y_{21}$  must equal zero in any conceivable solution; consequently, having  $y_{21}$  in the model is pointless. This approach minimizes the time; thus, performance of block model sequence is increased as a result. All in all, the author emphasizes that the variables of the upper blocks are important, minimizing the engagement of the lower blocks. Then, Brickey and Eurek (2014) contradicts that “lower bounds can be important, too: the scale and nature of production and processing operations in an open pit mine imply that large set-up costs accrue if operations are stopped and started repeatedly. Placing lower limits on production and processing reduces the potential for such effects”. Despite its importance to open pit block sequencing, it increases the time of performance. The author adds that a five-period test issue with no lower limits takes 176 seconds to solve using CPLEX, but 3,688 seconds when lower bounds are included.

Another technique is based on direct block scheduling (DBS), in which blocks are assigned extraction times directly through an underlying mathematical optimization problem. While this strategy is theoretically better, it suffers from the computing complexity associated with addressing mathematical problems, which may be quite large (P. H. A. Campos et al., 2018).

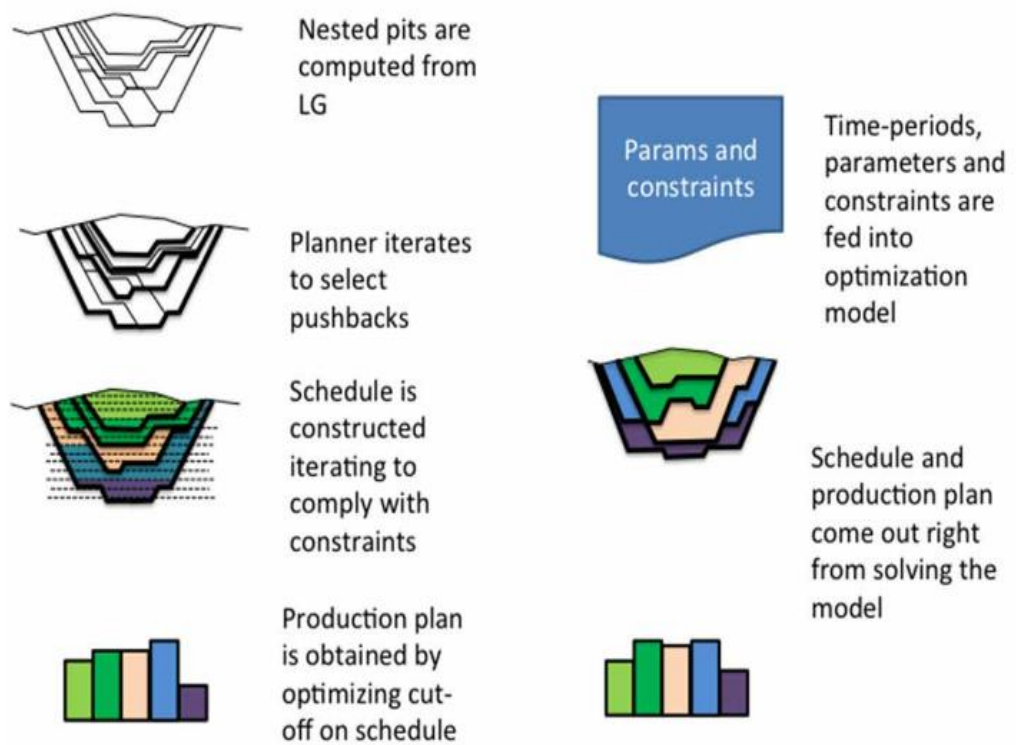


Figure 2. Traditional methodology versus direct block scheduling (P. H. A. Campos et al., 2018).

Figure 2 illustrates two primary methods for mine scheduling. On the left, is the conventional method, which depends on LG to build nested pits from which pushbacks are selected, and then production is scheduled. On the right is the DBS technique, which feeds all parameters and restrictions into an optimization model that generates a schedule and a production plan. It is critical to note that, the traditional technique requires the planner to assure compliance with constraints, optimization models cannot provide solutions that violate a constraint.

Another thing to mention is the importance of integer programming for open pit mines. Fricke (2006) defines that the main objectives of the integer programming are to optimize all aspects of a mine operation, from mine to plant to market; optimize life-of-mine schedules; optimize intermediate and short-term schedules following the life-of-mine schedule, and provide an efficient method for updating schedules as conditions change or new information

becomes available. However, Cullenbine et al. (2011) establish that this integer programming can be extremely difficult to solve, because: (i) a mine model may have from  $10^4$  to over  $10^6$  blocks, (ii) the time horizon may have  $T = 20$  periods or more, and (iii) the resulting model may have millions of variables and constraints. Integer programming is also used in the ultimate pit limit problem. Moreover, Mousavi et al., (2014) add that “the first gap is the lack of MBS models for a short-term horizon and the second gap is the lack of efficient solution approaches that are suitable for this problem”.

In addition, some authors provide other approaches to optimize open pit block sequencing and scheduling. Alah and Nogholi (2015) introduce Lagrangian relaxation and claim that the primary goal of this approach is to loosen up the subject by eliminating certain constraints, referred to as side constraints, and including them into the objective function through adjusted Lagrangian multipliers. Side constraints are limitations that make the issue very difficult to solve. Therefore, integrating some complicating constraints into the objective function could be done through the penalty factor. Instead of linear programming relaxation, the Lagrangian relaxation approach may be utilized to establish a lower limit on a branch and bound algorithm. Moreover, Tolouei et al. (2020) add that for mixed-integer programming problems, the Lagrangian relaxation (LR) approach is well-known as a viable mathematical solution. This approach is given in long term production scheduling (LTPS) using Lagrangian multipliers, which relax system constraints and present them to the objective function. After that, the relaxed problem is broken down into smaller, more manageable sub-problems that may be solved using dynamic programming by independent components. The Lagrangian relaxation could be also implemented in the sliding time window heuristic method. According to Cullenbine et al., (2011), the sliding time window heuristic (STWH) is based on solving a sequence of mixed-integer programs that have fixed variables in early periods, a full model representation in at least one middle period, and a relaxed representation in later periods. The use of Lagrangian relaxation is critical for computational efficiency. The author provides a method in which variables of mine production become more flexible and agrees that Lagrangian relaxation is a crucial factor in mine sequencing. Other authors provided a direct block

sequencing approach, which is more enhanced since extraction times for blocks are determined directly by an abstract mathematical optimization method. Nevertheless, it suffers from the computational complexity required to solve huge mathematical problems and could not perfectly replace Lerch-Grossman technique.

## 2.2 MINING RECOVERY AND DILUTION

Mining projects are inherently uncertain and risky. This is because market circumstances, resource models, and mining parameters like tonnages, grades, and dilution all remain unpredictable. To mitigate investment risk, mining corporations devote significant time and money in studies that forecast grades and tonnages, as well as mining conditions and costs. Due to the difficulty of monitoring certain critical design characteristics, such as dilution, some elements might be overlooked. Revenues are calculated using the tonnage and grade of ore established during the mine design. To compute the tonnage and grade, a resource model, dilution, and mine recovery parameters are used. It could be observed that the involvement and consideration of mining recovery and dilution is crucially vital in the mining industry. The following section is going to provide the possible solutions on optimizing the mining recovery and dilution. One thing to mention is that a high early cut-off grade will result in significant ore loss, while a low late cut-off grade would result in excessive waste rock and raise mining costs (Zhang et al., 2021). Dilution is a term that refers to waste material that is not separated from ore during the mining process and is mined alongside ore. This waste is combined with ore and sent to a processing facility. Dilution increases ore tonnage while lowering the grade. **Dilution is defined as the ratio of waste mined and supplied to the mill to the total amount of ore and trash processed. It is often stated as a percentage. The dilution could be expressed as the equation (2) below:**

$$Dilution = \frac{Tonnage\ of\ Waste}{Tonnage\ of\ Ore + Waste} \times 100\% \quad (2)$$

Dilution occurs in two distinct places when referring to a mining block. Occasionally, waste inclusions or low-grade pockets of ore occur inside a mining block and are unable to be separated and are unavoidably mined together with the mining block. This process is referred to as internal dilution. Internal dilution is difficult to prevent, if not impossible. Internal dilution occurs in varying degrees in various kinds of deposits. Internal dilution is influenced by lithology and grade distribution. External dilution, sometimes termed contact dilution, refers to waste that is mined outside of the orebody inside the mining block. External dilution varies according to geology, orebody form, drilling and blasting procedures, operation scale, and equipment size. This is the form of dilution that is controllable with the use of appropriate equipment and mining methods. Figure 3 demonstrates a mining block in an open pit mine bench with several sorts of dilutions.

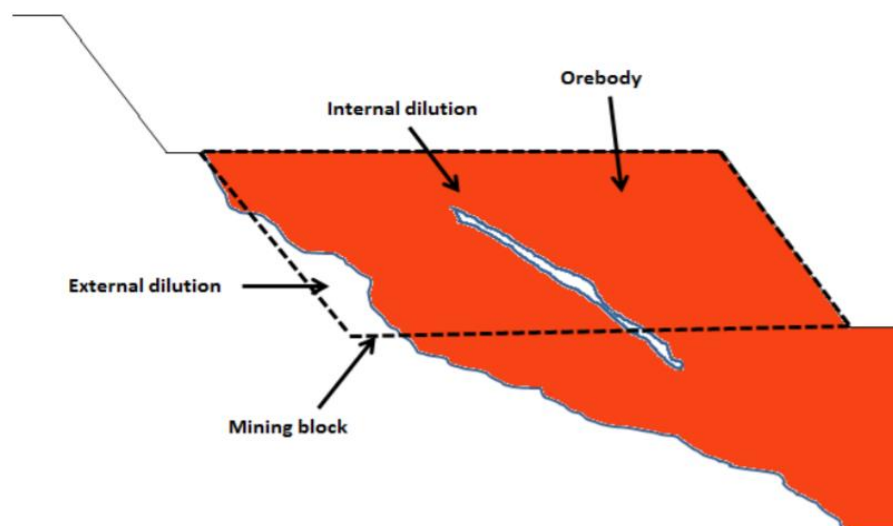


Figure 3. Open pit scheme and types of dilution (Ebrahimi, 2013).

It is crucial to understand the impact of the dilution to the economic segment of the open pit mine project. Ebrahimi (2013) claims that one of the primary outcomes of dilution is a decrease in the grade of mill feed. A lower feed grade equates to a lower revenue. Dilution may lower the grades of marginal grade ore to the point where processing becomes uneconomic; in

other words, dilution can transform an ore block into waste block. The equation 2 below may be used to determine the feed grade after dilution.

$$Feed_g = \frac{ore_g + waste_g \times dilution}{1 + dilution} \quad (3)$$

Secondly, dilution results in a loss of energy and resources utilized in the processing plant to treat the waste part of the feed. As a consequence, the unit operating cost of the mill rises according to the dilution factor. For instance, in a project with an expected processing cost of \$18/t, a 10% dilution implies that \$1.80 is spent processing trash in the mill for every ton of feed. For a 30,000 ton per day plant, this quantity of dilution equates to a daily loss of \$54,000. Thirdly, occupying part of the processing capacity by sending waste rocks to the plant prolongs mine life. As a result, it delays cashing the value of mineable resources on time as planned. A longer mine life lowers the net present value (NPV) and internal rate of return (IRR). For example, consider a mine that has the potential to generate \$20M/year net revenue by milling a certain amount of ore for up to 10 years. This is after \$100M initial capital investment. Assuming a 10% dilution the mine life increases to 11 years from 10 years. With a simple calculation, it is possible to compare mine economics for two cases of mining operation, with dilution and without dilution. For this example, there will be a 21.0% decrease in NPV (at 10% discount) and an 8.6% decrease in IRR after 10% dilution. Although dilution cannot be avoided, it can be quantified and then controlled. In most cases, quantifying dilution is so challenging that calculating it will become the main part of the solution. In mining operations, to calculate dilution the information obtained from samples on conveyor belts (after crusher) can be compared with resource/reserve models that are developed using drill data. This is the best way of calculating the actual dilution occurring in a mine. The accuracy of the calculation of course depends on the accuracy of sampling and resource modeling. In the case of mining studies, where no operation data are available, suitable techniques must be used to estimate dilution. Quantifying dilution during the study stage is necessary to have a better economic evaluation of the project. In addition to achieving a more accurate economic evaluation, quantifying dilution helps to improve mine design. If the study shows significantly high dilution, it is a

starting point to mitigate it by changing the mine plans. Dilution can be reduced by adjusting the mine design and operation-related factors to best match the deposit-related factors. For example, by reducing bench height it may be possible to mine more selectively. Obviously, for this case, we must also realize that reducing the bench height will increase unit production cost due to the smaller scale of operation. The bottom line is that to improve the economy of a mine a series of factors such as bench height, selectivity, and production rate must be optimized together. This paper tries to introduce a technique for estimating dilution in open pit mines using computer software as well as proposing a standard procedure for the work. (Ebrahimi, 2013).

Marinin et al. (2021) introduce a possible solution for optimization in mining production. The Mine-to-Mill approach focuses on developing an integrated strategy for optimizing production, ore crushing, and subsequent grinding to minimize ore crushing costs and boost production profitability. The purpose of this connection is to optimize all stages of processing. In addition, the author claims:

“Mine-to-mill optimization's ultimate objective is to maximize the energy efficiency of rock breaking by maximizing blast fragmentation. In mines, crushing and grinding are among the most energy-intensive operations. Rock breaking accounts for around 30%–60% of overall energy usage in mines. As a result, this process has an effect on not just energy consumption, but also overall mining productivity. This process may be enhanced via the use of mine-to-mill optimization.”

All mining and processing activities in gold mines require several consecutive steps. These steps should be mutually reinforcing, with one procedure influencing another. It is not sufficient to optimize each function independently to improve the whole process. The whole mineral extraction process should be considered. There are two distinct forms of mine-to-mill integration. One is operational, while the other is physical.

Operational integration focuses on the following:

- monitoring processes via the use of drill and shovel technologies.

- optimizing blast fragmentation.
- optimizing communication processes.
- improving factory monitoring, particularly of the handling system in the pit and ore.

Physical integration focuses on fragment size categorization, grade control improvement, sorting, and mill feed quality enhancement (Marinin et al., 2021).

## **2.3 CASE STUDY**

### **2.3.1 Case study 1**

Rosebel Gold Mines is a gold mine complex located in Suriname. The case study considers three deposits: Rosebel Mine, Pay Caro Mine, and Royal Hill Mine. Each deposit consists of blocks of  $16 \times 12 \times 9$  m, for a combined total of 1.07 million mining blocks: 0.26 million at Rosebel Mine, 0.38 million at Pay Caro Mine, and 0.43 million at Royal Hill Mine. The material uncertainty is quantified using 10 stochastic simulations of the gold grades per mine (LaRoche-Boisvert & Dimitrakopoulos, 2021). The drill and blast cost, loading cost, dump maintenance cost, and closure cost are all part of the mining cost, whereas the overall processing cost is broken down into processing cost, transportation cost, and storage cost to account for the various expenses involved with administration and maintaining capital with the many sorts of materials.

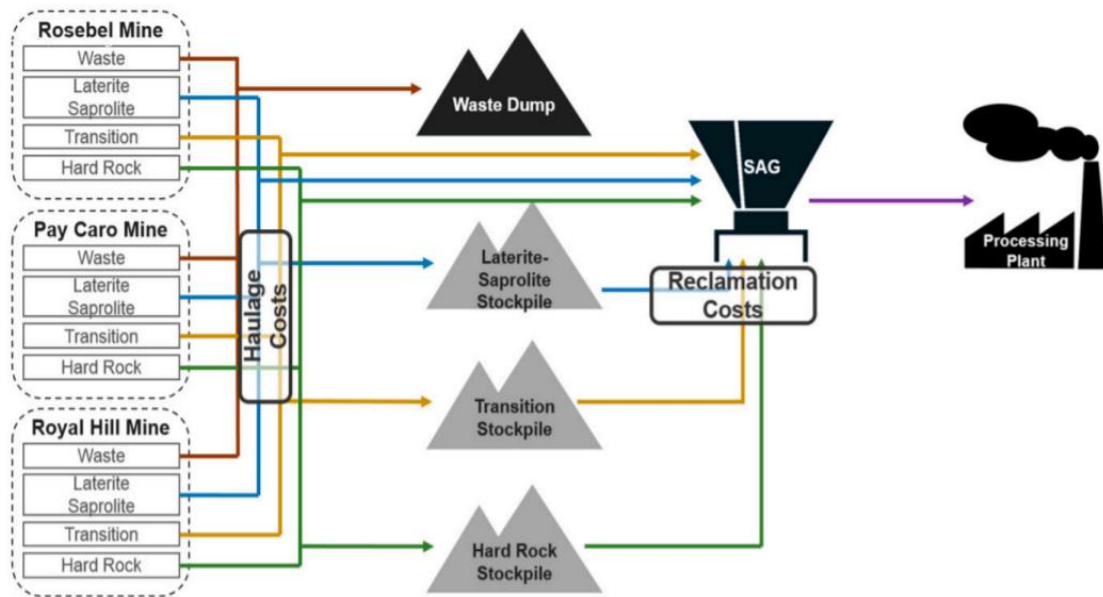


Figure 4. The schematics of the process of Rosebel gold mine complex (LaRoche-Boisvert & Dimitrakopoulos, 2021)

Figure 4 demonstrates the flow of the rock mass from three mines (Rosebel, Pay Caro and Royal Hill mine). The recovered ore material might be delivered straight to the processor or to the appropriate stockpile. In the early years, the laterite-saprolite material was stockpiled to a larger extent, and it was recovered over time. The hard rock material is stored to a higher degree at the conclusion of the mining complex's existence, whereas the transition material is rarely stockpiled. The SAG mill crushes ore that is recovered from stockpiles or supplied straight to the processor.

Table 1. Capacity and Scheduling constraints for developing scheduling (LaRoche-Boisvert & Dimitrakopoulos, 2021)

Constraints	Capacity
Mining Capacity (years 1–5)	67.3 Mt/y
Mining Capacity (years 6–18)	74.0 Mt/y
SAG Mill Capacity	876 h/y
Processing Capacity	8.83 Mt/y
Constraint	Distance
Smoothness	48 m
Max sink rate	63 m

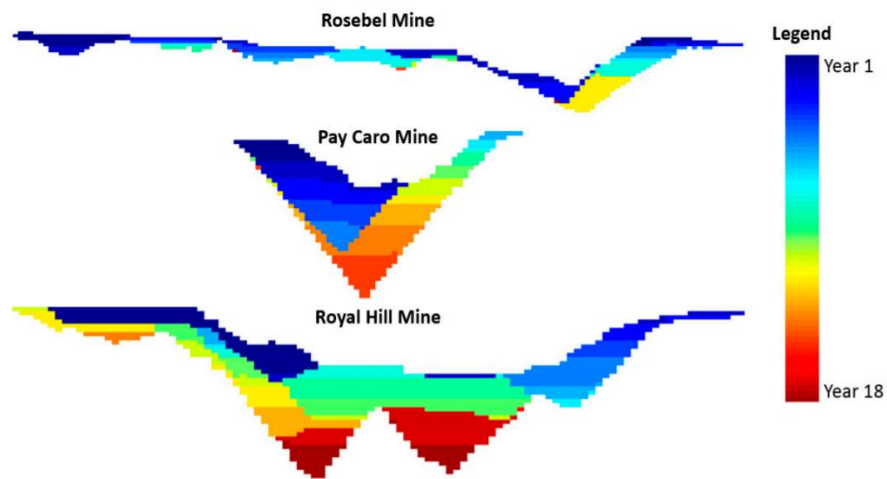


Figure 5. Stochastic life-of-asset production schedules at the three mines at the RGM mining complex (LaRoche-Boisvert & Dimitrakopoulos, 2021)

Figure 5 illustrates the schedule to produce three distinct deposits of the complex. The production schedule is developed by the constraints shown in Table 1.

### 2.3.2 Case study 2

The following case study was conducted by Saavedra-Rosas (2016). The examples were used from Minelib (Espinoza et al., 2013), library of test problems for open pit mining problems. Some of which corresponds to real-world mining projects. In terms of size, they were more suited for our research. Because of the cases is complicated and took a long time to compute (Saavedra-Rosas, 2016). This block model comprises 53 271, 30x30x30 m blocks, however this number may be lowered by removing blocks that are not accessible from the block model. A 45° slope angle and seven layers of precedence above a specific block determine the wall slope requirements.

Table 2. Main economic and technical parameters (Saavedra-Rosas, 2016).

<b>Economic and technical parameters in the Marvin instance</b>		
<b>Parameter</b>	<b>Value</b>	<b>Unit</b>
Copper price	3.02	US\$/lb
Gold price	1132	US\$/oz
Copper recovery	0.88	-
Gold recovery	0.60	-
Selling cost	0.60	US\$/lb
Processing cost	10	US\$/ton
Reference mining cost	1.8	US\$/ton
Increment mining cost	0.002	US\$/ton · m
Slope angle	45	degrees
Time horizon	7	Years
Discount rate	0.10	-
Mining capacity	60 000 000	t/a
Processing capacity	20 000 000	t/a
Minimum exposed ore (as metal)	100 000	t/a

Copper and gold are the two metals of importance in this deposit, and each block has its own set of characteristics, such as tonnage and grade. Moreover, parameters for the given case study such as commodity price, recovery, mining capacity and processing capacity, are shown above.

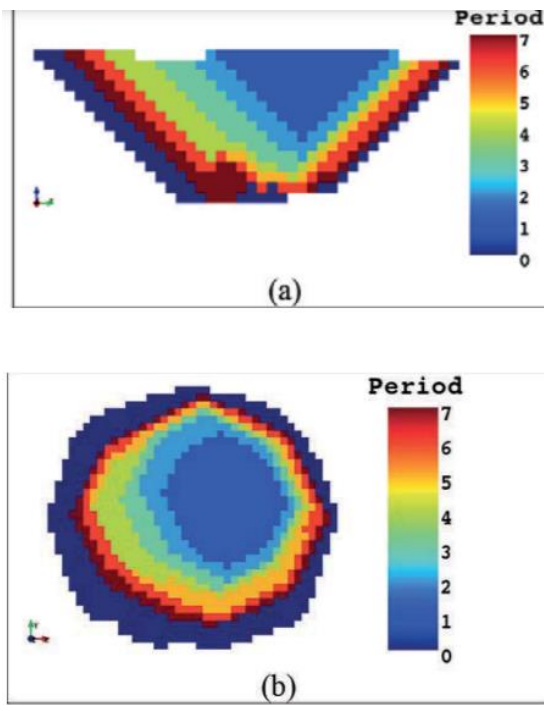


Figure 6. Block Schedules for a 7-year period (Saavedra-Rosas, 2016).

Figure 6 above shows the pits created while scheduling the Marvin example, with a YZ-section view and a horizontal plane for a schedule derived via open pit block sequencing (OPBS). The colors represent the different times when the blocks are removed.

Table 3. Production plans for each period (Saavedra-Rosas, 2016).

<b>Comparison of production plans for the Marvin case study</b>				
<b>Period</b>	<b>OPBS</b>			
	<b>Grade %</b>	<b>Ore tons</b>	<b>Total tons</b>	<b>Exposed tons</b>
1	1.03	19 994 670	59 989 965	0
2	1.14	19 971 010	49 490 568	359
3	1.05	19 980 880	40 052 602	1 462
4	1.02	19 985 340	44 985 249	4 719
5	0.97	19 999 920	49 166 274	7 569
6	0.92	19 999 290	52 191 380	6 254
7	0.88	15 535 850	46 060 989	-
Total		135 466 960	341 937 027	20 363

Production plans for the case study is demonstrated above in Table 3. Grade, ore, and waste tons are determined for each period of time. In terms of applicability, the presented model has a lot of promise, but more algorithmic research is needed to enhance the computational execution time in the case of very large instances (Saavedra-Rosas, 2016). However, it's important to note that the focus of this case study was on introducing the concept and providing the accompanying model.

### 2.3.3 Case study 3

The case study was produced using a block model of a real iron ore mine in Brazil. This model consists of 38 172 regular blocks of 50 m 50 m 20 m in size (P. Campos et al., 2018). Along with its three-dimensional coordinates, each block includes the following important attributes: tonnage, iron grade, waste, and possible destination (processing plant or waste dump). Economic parameters such as iron price, iron recovery, selling cost, processing cost, and mining cost are considered for economic analysis.

Table 4. The strategic planning of the whole project produced the life-of-mine production plan (P. Campos et al., 2018).

<b>Economic and technical parameters</b>		
<b>Parameter</b>	<b>Value</b>	<b>Unit</b>
Iron price	70	US\$/t
Iron recovery	0.9	-
Selling cost	18	US\$/t
Processing cost	9.45	US\$/t
Mining cost	4.5	US\$/t
Discount rate	0.1	-
Mining capacity	55	Mt/a
Processing capacity	36.5	Mt/a
	<b>Bearing</b>	<b>Slope</b>
Slope angle	0–120°	45°
	120–240°	35°
	240–360°	30°

In the following case study, three approaches of block sequencing were performed. The first one is a conventional method of scheduling using a renowned software package in the mineral industry (Deswik). The objective was to calculate the tonnage of ore and waste and Net Present Value (NPV) of the first five years. Based on the results, the mass extracted in the first five years (about 281 Mt) was assumed to be medium-term sequenced in the software program. These blocks are outlined in red in Figure 7, while the blocks belonging to the final pit are represented in green and the other blocks in blue.

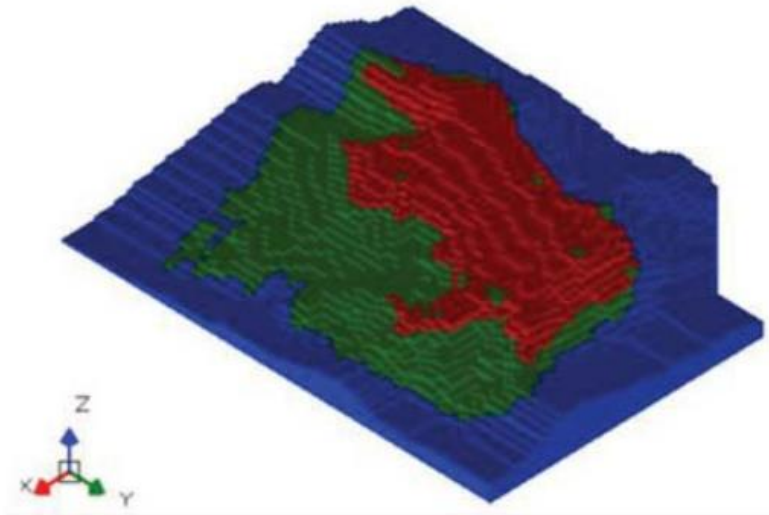


Figure 7. A 3D view of the block model (P. Campos et al., 2018).

Then, the red blocks were rescheduled using the Deswik software to create an annual plan that corresponds to previously set intermediate plan. Figure 8 illustrates this schedule in which the pink blocks indicate the blocks to be removed during that particular period and the green blocks refers to the block to be removed at another period.

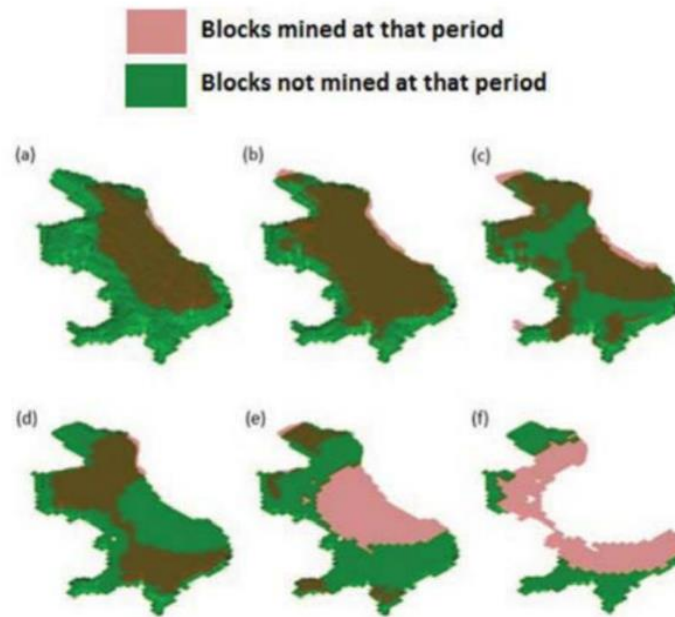


Figure 8. Annual scheduling for the red blocks (P. Campos et al., 2018).

The second approach was completed by using direct block sequencing. To appropriately run the sequencing, the operational and physical constraints such as the horizontal and vertical rates of advance, the minimum mining width, and the maximum number of mining fronts, as well as resource characteristics such as the mining rate, utilization, and availability should be implemented. The results of the case study suggest that the DBS defers overburden removal and attempts to reduce the undiscounted value over time while raising the stripping ratio. Due to the limitation of mining all blocks, the last phase generates more waste and has a negative economic value, lowering the cumulative NPV. Scheduling through DBS plan results in a 10.57% in NPV as compared to conventional scheduling. However, this strategy has unfeasible scheduling results, and there is no way to determine if the blocks have any real benefit. However, combination of the sequencing methods improves the NPV by 0.43 percent; this gain is practical and achievable.

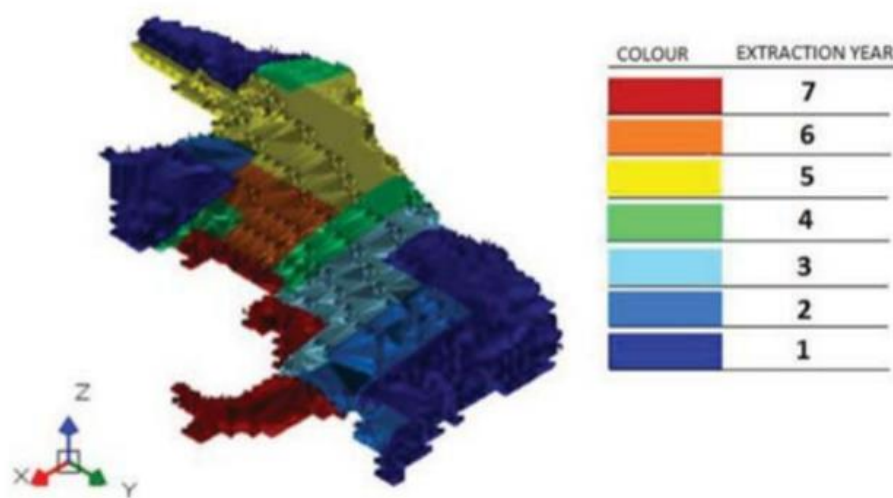


Figure 9. Block sequencing by using Direct Block Sequencing (DBS) (P. Campos et al., 2018).

### 3. METHODOLOGY

The following research part demonstrates the approaches to analyze mining block sequences and scheduling. The first part defines the mathematical model - linear programming of the block sequencing optimization. This mathematical model is considered as a root function for sequencing and scheduling processes in the mining software. In the second part, mine block sequencing and scheduling simulations were run using Datamine Studio NPVS software.

#### 3.1 Justification of selected methods

Generally, there is no mathematical technique capable of discovering the optimal solution to the block sequencing problem. However, algorithms are available that provide useful alternatives, provided many parameters has been implicitly or explicitly determined under the supervision of a mining planner and depending on the amount and quality of the model's input parameters. We begin by addressing the issue of obtaining the optimal final pit limit for a mine

using a collection of all feasible net values and the set of blocks that must initially be extracted, in accordance with the pit slopes, to expose the block under consideration. The ultimate pit is defined as the contour formed by extracting a volume of material with a total maximum net value that also meets the pit slope criteria. While the floating cone approach was a common method for creating the final shape, it did not always provide appropriate results. In research from Bastante et al. (2004), a solution to the issue was discovered in the graph-theoretic approach developed by Lerchs and Grossmann (1965). After defining the phases, we construct the production schedule. While most of the software packages use heuristic search approaches to determine the optimal temporal extraction sequence, some utilize linear programming techniques or a mix of the two.

### 3.2 Numerical Model

As it was mentioned before, linear programming is the study of solving mathematical optimization problems in which at least some of the decision variables must have integer values. Mathematical models involving integer decision variables are used in a wide variety of applications, most notably when yes/no judgments are required. It is crucially important to understand the working principles (mathematical model) of the common modern software. The long-term scheduling problem for open pit mining is concerned with accurately picking the blocks to mine to optimize the process's total profit over a certain time period. According to Kumral (2012), the conventional mine production planning is formulated as follows (objective function):

$$\text{Max } f(x) = \sum_{i=1}^T \sum_{j=1}^N V_{ij}(m)x_{ij} \quad (3)$$

$$m = \begin{cases} 1 & \text{if the grade of block } j \geq \text{cut} - \text{off}_i \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$V_{ij}(1) = (\text{price} \times \text{recovery} \times \text{ore tonnage of block } j \times \text{grade of block } j) - (\text{mining cost} + \text{processing cost} \times \text{tonnage of block } j) \times (1 + n)^{-i} \quad (5)$$

$$V_{ij}(0) = -(\text{mining cost} \times \text{tonnage of block } j) \times (1 + n)^{-i} \quad (6)$$

Decision Variable:

$$x_{ij} = \begin{cases} 1 & \text{if the block } j \text{ is produced in period } i \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Where N is the number of blocks, T is the number of periods,  $V_{ij}$  (m) is the present value of block j in period i for classification m,  $x_{ij}$  is a binary variable, n is discount rate.

Besides the objective function, it is also important to subject it to the specific constraints. Typically, the constraints related to block accessibility, mining and milling capabilities, mill feed and concentrate grades, extraction equipment capacities, and physical and operating requirements such as the minimum width necessary for machinery. Osanloo et al., (2008) provides constraints functions for related areas:

$$G_{min}^{tm} \leq \sum_{i=1}^N g_i \times TB_i \times x_i^{tm} / \sum_{i=1}^N TB_i \times x_i^{tm} \leq G_{max}^{tm}, \text{ for } t = 1, 2, \dots, T \text{ and } m = 2, 3, \dots, M \quad (8)$$

$$PC_{min}^{tm} \leq \sum_{i=1}^N TB_i \times x_i^{tm} \leq PC_{max}^{tm}, \text{ for } t = 1, 2, \dots, T \text{ and } m = 2, 3, \dots, M \quad (9)$$

$$MC_{min}^t \leq \sum_{i=1}^T \sum_{j=1}^N TB_i \times x_i^{tm} \leq MC_{max}^t, \text{ for } t = 1, 2, \dots, T \quad (10)$$

where T is the maximum number of scheduling periods, N is the total number of blocks to be scheduled, i is the block index,  $x_i^{tm}$  is the proportion of block i to be mined in period t as a processing type m,  $g_i$  is the average grade of block i,  $TB_i$  is the total tonnes of material in block i.  $G_{min}^{tm}/G_{max}^{tm}$  is the minimum/maximum average grade of the material m sent to the mill in period t,  $PC_{min}^{tm}/PC_{max}^{tm}$  is the minimum/maximum processing capacity of material type m in any period,  $MC_{min}^t/MC_{max}^t$  is minimum/maximum mining capacity in any period.

### 3.3 Software computation

To run software simulation of sequencing, geological block model referred to real-world gold-copper deposit is considered as a main input of the software (Madani, 2021). The mining

areas were defined using the lithological units and geotechnical features of the rock. To begin, Datamine Studio NPVS was used to do a preliminary pit optimization to evaluate the possible placement of the ultimate pit limit. The block model is already produced for both Copper and Gold in Datamine Studio RM. However before running the software simulation, firstly the economic parameters of base case, optimistic and pessimistic should be set to derive economic block model. Annual discount rate is set to 10%. Tables 5, 6 and 7 illustrate the economic parameters of project scenario.

Table 5. Economic parameters of base case (Madani, 2021).

Rock type	Element	Price	Selling cost		Mining cost (\$/t)	Processing cost (\$/t)
Ore	Gold (/g)	\$ 41.80	2.5%	\$ 1.05	\$ 5.00	\$ 36.91
	Copper (/t)	\$ 6,410.00	2.5%	\$ 160.25		
Soil	-	-	-	-	\$ 3	-
Weathered rock	-	-	-	-	\$ 4	-
Fresh rock	-	-	-	-	\$ 4.75	-

Table 6. Economic parameters of optimistic scenario (Madani, 2021).

Rock type	Element	Price	Selling cost		Mining cost (\$/t)	Processing cost (\$/t)
Ore	Gold (/g)	\$ 50.16	2.5%	\$ 1.25	\$ 4.00	\$ 29.53
	Copper (/t)	\$ 7,692.00	2.5%	\$ 192.30		
Soil	-	-	-	-	\$ 2.40	-
Weathered rock	-	-	-	-	\$ 3.20	-
Fresh rock	-	-	-	-	\$ 3.80	-

Table 7. Economic parameters of pessimistic scenario (Madani, 2021).

Rock type	Element	Price	Selling cost		Mining cost (\$/t)	Processing cost (\$/t)
Ore	Gold (/g)	\$ 33.44	2.5%	\$ 0.84	\$ 6.00	\$ 44.29
	Copper (/t)	\$ 5,128.00	2.5%	\$ 128.20		
Soil	-	-	-	-	\$ 3.60	-
Weathered rock	-	-	-	-	\$ 4.80	-
Fresh rock	-	-	-	-	\$ 3.80	-

The second step in software simulation is to adjust geotechnical and other technical restriction parameters. In this section, the recovery information was adjusted as well.

Table 8. Recovery formulas (Madani, 2021).

Element	Recovery formulas
Gold	$\text{If } (Au < 1, 0, (0.0207 * (Au^{**3}) - 1.3576 * (Au^{**2}) + 22.58 * (Au) - 17.204) / 100)$
Copper	$\text{If } (Cu < 0.1, 0, (1713 * (Cu^{**3}) - 2236 * (Cu^{**2}) + 987.83 * (Cu) - 76.667) / 100)$

The formulas identifies that the recovery of grade less than 1 g/t is equal to zero. However, grades above 1 g/t are recovered by the above formula. Specifically, higher grade blocks could be recovered better, while the low-grade blocks' recovery is slightly less than the higher ones. The same is for copper, the recovery for grades less than 0.1% is equivalent to 0.

While the higher grades are recovered by the given formula. Figures 10 and 11 shows graphical interpretations of recovery with respect to the grade.

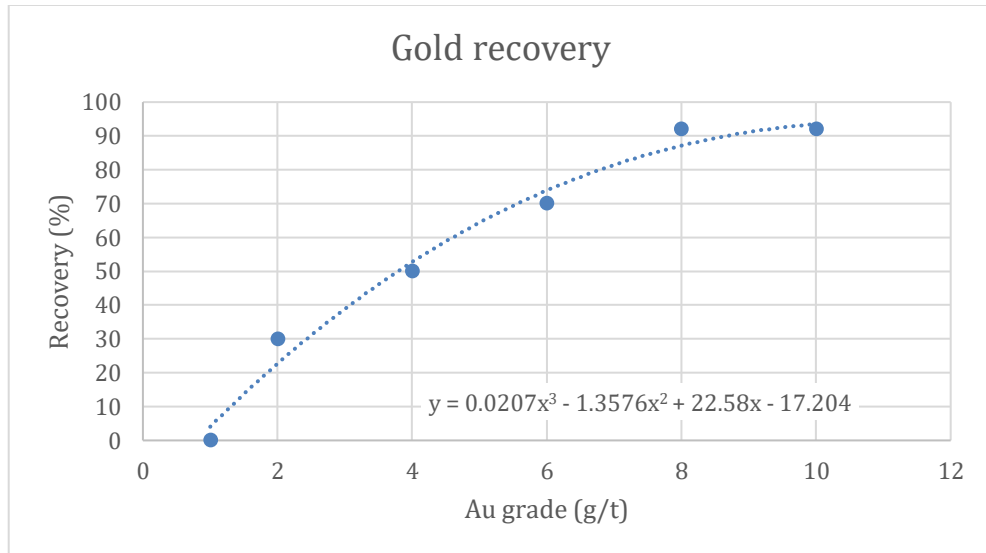


Figure 10. The graph of Au recovery.

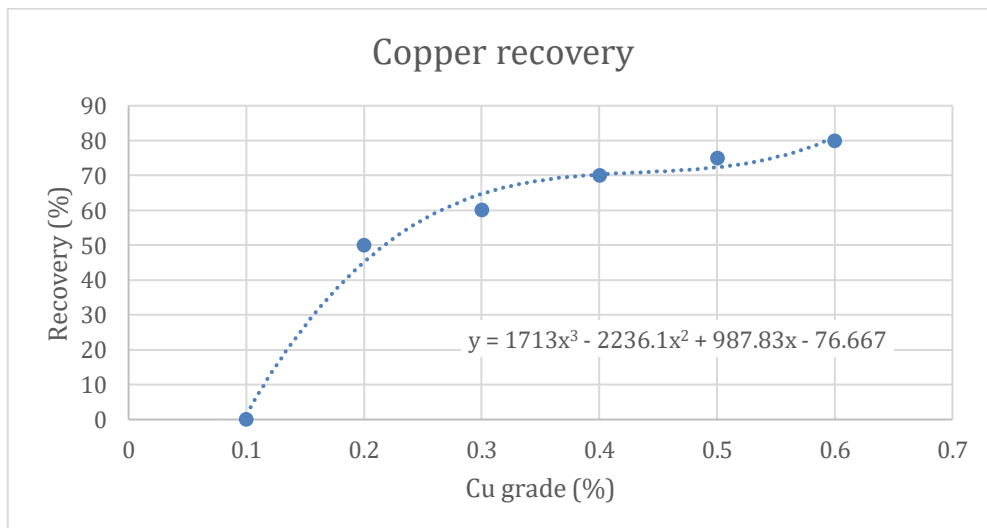


Figure 11. The graph of Cu recovery.

To obtain an ultimate pit limit, overall slope angles were adjusted for the different rock types. The following slope angles in Table 7 allow to find the highest possible cashflow within a pit limit. For pushback, mining width should be adjusted properly for pushback generation. The movement of this equipment (shovel truck) at the mine's bottom usually requires a minimum bottom width of 30 meters (Nancel-Penard & Morales, 2021).

Table 9. Geotechnical information of block model (Madani, 2021).

<b>Material</b>	<b>Overall angle (°)</b>
Soil	25
Fresh rock	55
Weathered rock	45
Ore	55
<b>Mining width</b>	<b>30 m</b>

## 4. RESULTS

### 4.1 Base Scenario

The main outputs of gold-copper open pit mine software simulation are production scheduling, economic cut-off grade, life of mine, generated Lerchs-Grossman phases, extraction sequence, pushbacks and finally, economic output of the project. Figures 13 - 16 demonstrate the mining pushbacks of the project. The software provided four pushbacks for the entire time horizon of the project.

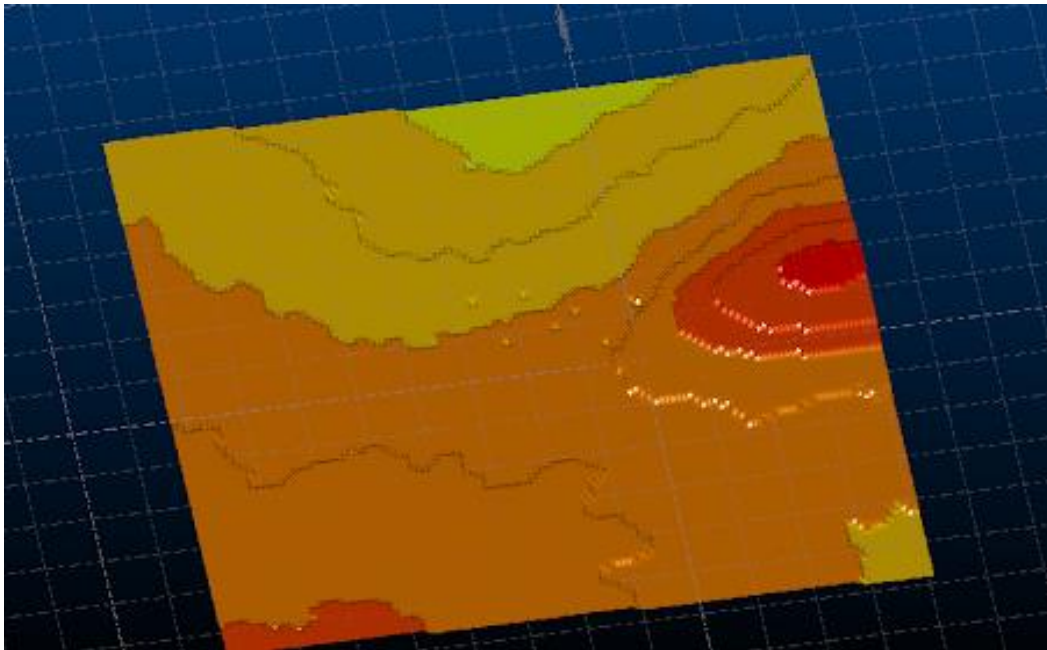


Figure 12. Side view before mining operations.

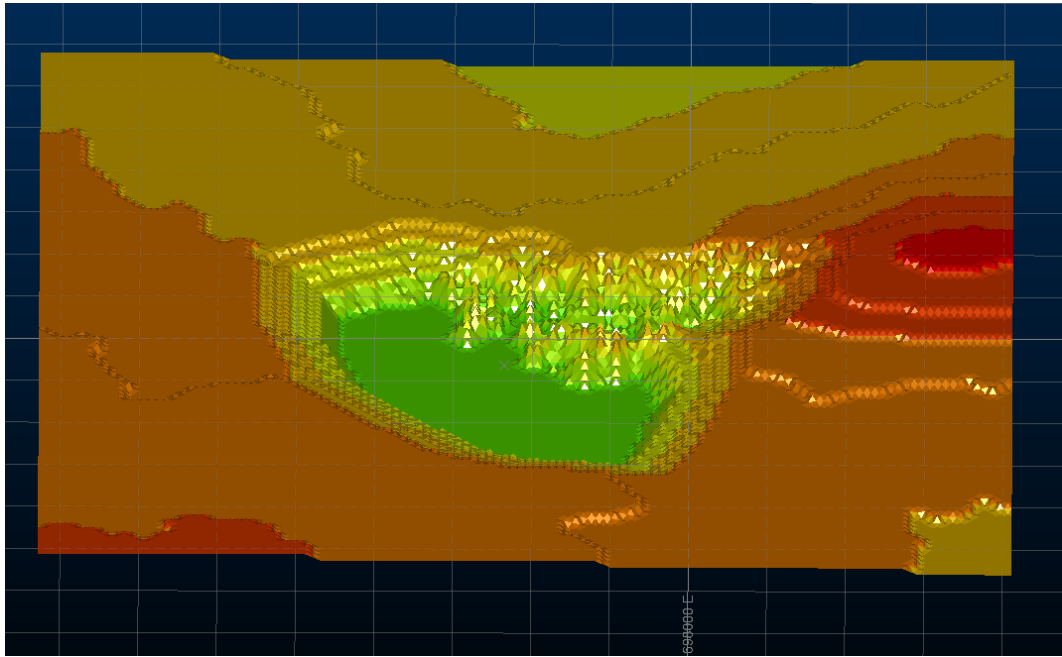


Figure 13. Side view of pushback no. 1 (Base Case).

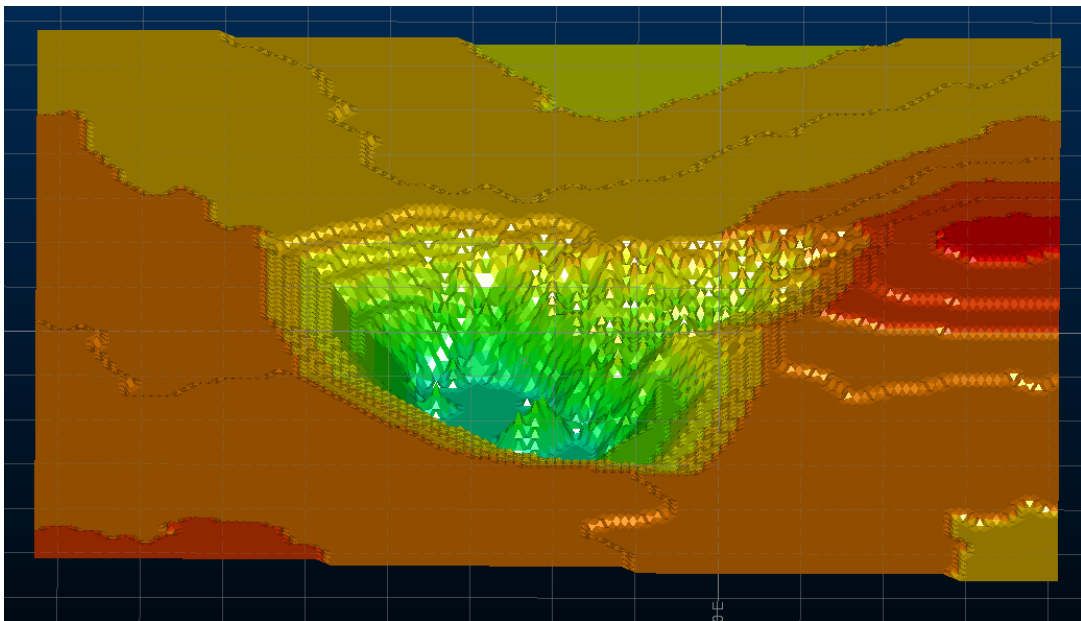


Figure 14. Side view of pushback no. 2 (Base Case).

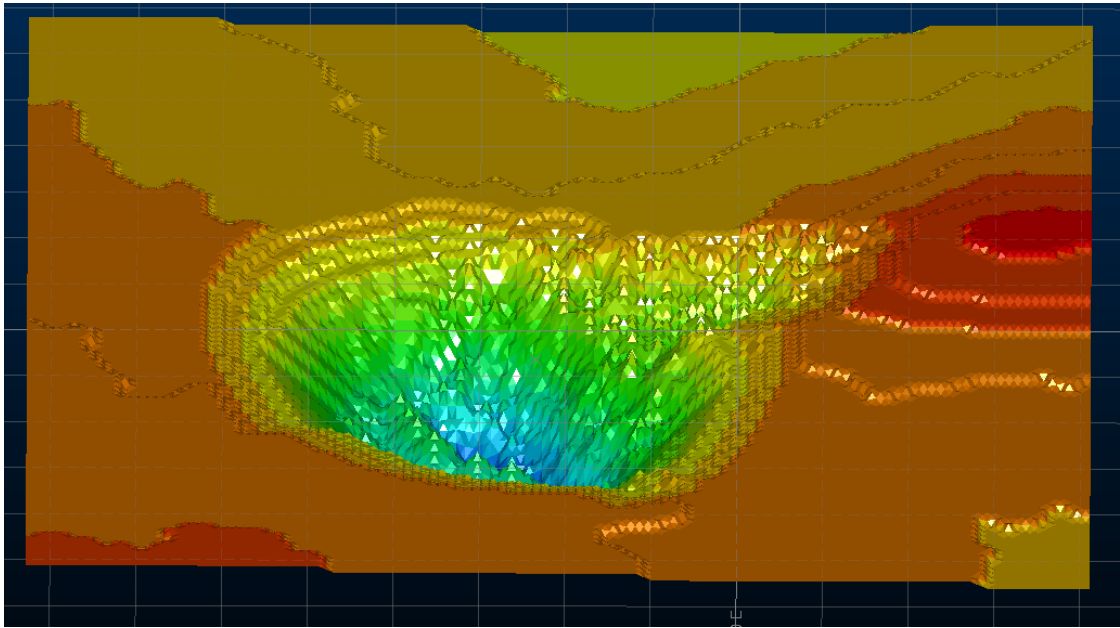


Figure 15. Side view of pushback no. 3 (Base Case).

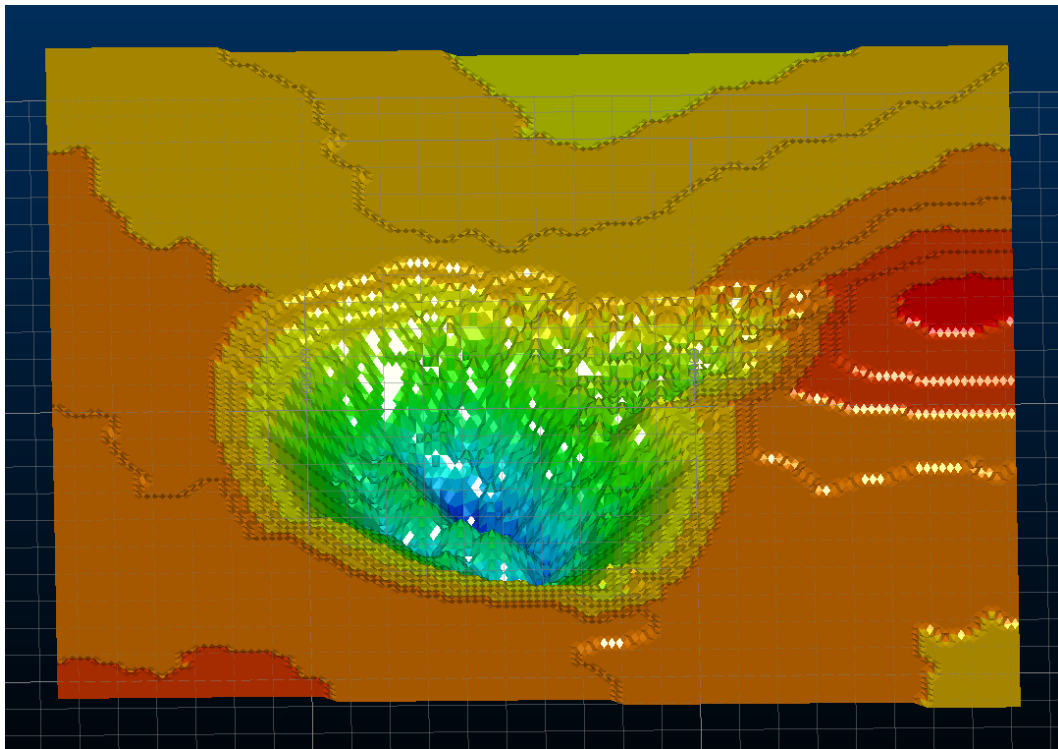


Figure 16. Side view of pushback 4 (Base Case).

Moreover, tonnage of ore and waste are demonstrated in Table 8 below.

Table 10. Ore, waste, and profit generated within each pushback (Base Case).

<i>Pushbacks</i>			
Pushback	ORE	Waste	Profit
1	4,812,600	26,607,700	586,657,659
2	5,967,000	10,640,000	820,172,602
3	3,268,200	27,310,600	352,432,072
4	3,564,600	19,224,000	446,528,618

After determining the pushback designs, the final pit limit could be obtained through the software. The results of the pit limit are shown in Figures 17 and 18.

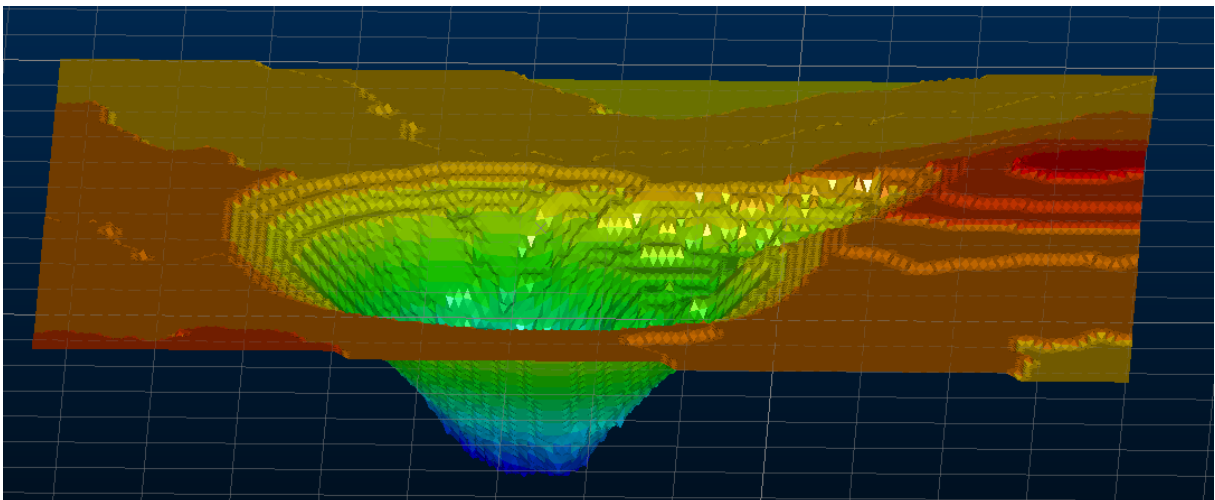


Figure 17. Side view of the pit limit (Base Case).

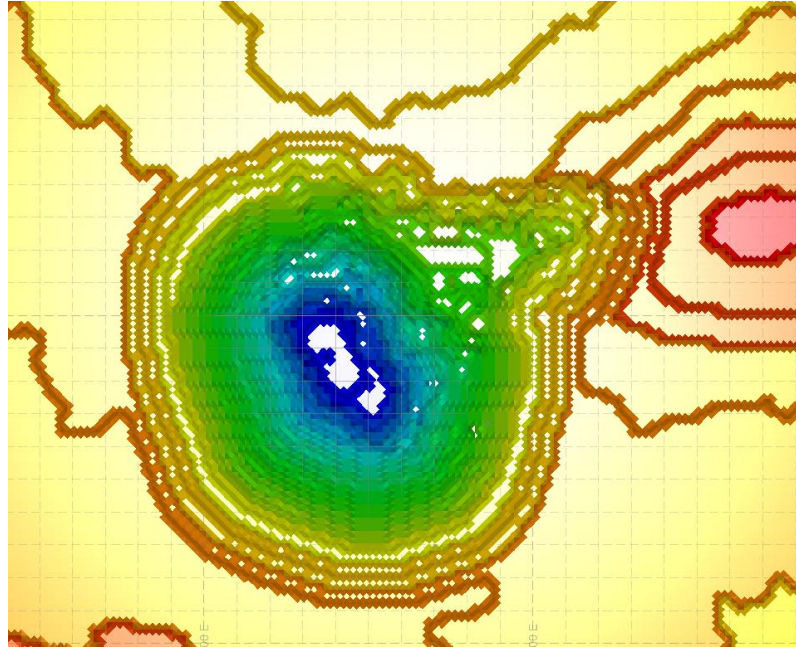


Figure 18. Plan view of pit limit (Base Case).

The lifetime of the project is predicted to be 10 years in accordance with the highest net present value of the project. In other words, extracting blocks after 10 years is not economically profitable. Table 11 below shows the results of simulation of 10 years of production – revenue, mining and processing costs for the entire project.

Table 11. Scheduling results of the project (Base Case).

<i>Schedule</i>		
	Lifetime	NPV at per Year discount
	Years	\$
	10	610,563,364

To be more precise, those 10 years are then split into one year time horizon (Table 12). Specific values of rock tonnes, revenue, mining, and processing cost, NPV and tonnage of other types of rocks.



input data included two elements – gold and copper, it provided two distinct economic cut-off grades for the project. Table 14 presents the results of the economic cut-off grade (COG).

Table 14. The cut-off grades of the base case.

Au Economic COG	2.6743	g/tonne
Cu Economic COG	0.6481%	Percent

Finally, economic results on the entire project are shown in Table 15 and in Figure 20 below. Moreover, block count and total mass of ore and waste are provided as well. As earlier mentioned, the trend of NPV (red line) is supposed to decrease within Pit no. 89.

Table 15. Economic output of the simulation (Base Case).

Global Stats													
Cash	Revenue	Minimum	Maximum	Process Cost	Minimum	Maximum	Mining Cost	Minimum	Maximum	Net Value	Ore Value		
	2,316,226,171	144,736	1,556,381	752,843,871	143,949	245,349	4,700,398,025	5,400	19,500	(3,137,015,725)	1,485,791,800		
	Block Count	Mass											
ORE	3,979	15,518,100											
Waste	409,605	1,062,434,900											
Total	413,584	1,077,953,000											
Strip Ratio	68.4642												
ORE Stats													
	Mass	Au	Au Min	Au Max	Cu	Cu Min	Cu Max	Au R	Au R Min	Au R Max	Cu R	Cu R Min	Cu R Max
	tonnes	g	g/tonne	g/tonne	tonnes	Percent	Percent	g	g/tonne	g/tonne	tonnes	Percent	Percent
ORE	15,518,100	79,794,620	1.8980	9.9856	29,290	0.0003%	0.5994%	54,449,945	0.3968	9.3377	15,504	0.0001%	0.4855%
Waste Stats													
ORE (w)	28,446,600												
WEATH	355,102,000												
SOIL	94,024,800												
FRESH	584,861,500												
Total	1,062,434,900												

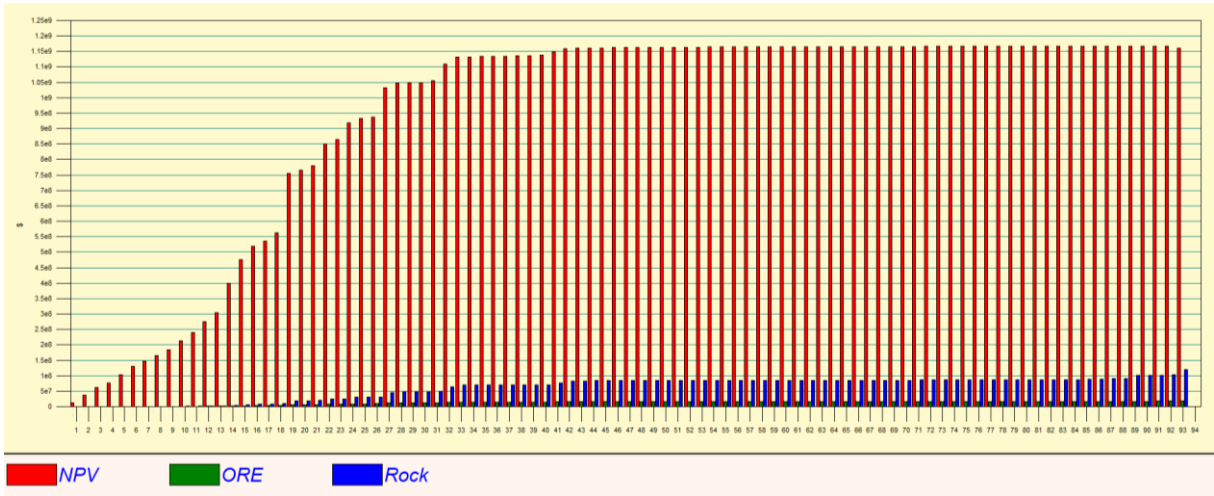


Figure 19. The histogram of NPV, ore and waste tonnage (Base Case).

## 4.2 Optimistic Scenario

Figures 20 - 22 demonstrate the mining pushbacks of the project. The software provided three pushbacks for the optimistic scenario.

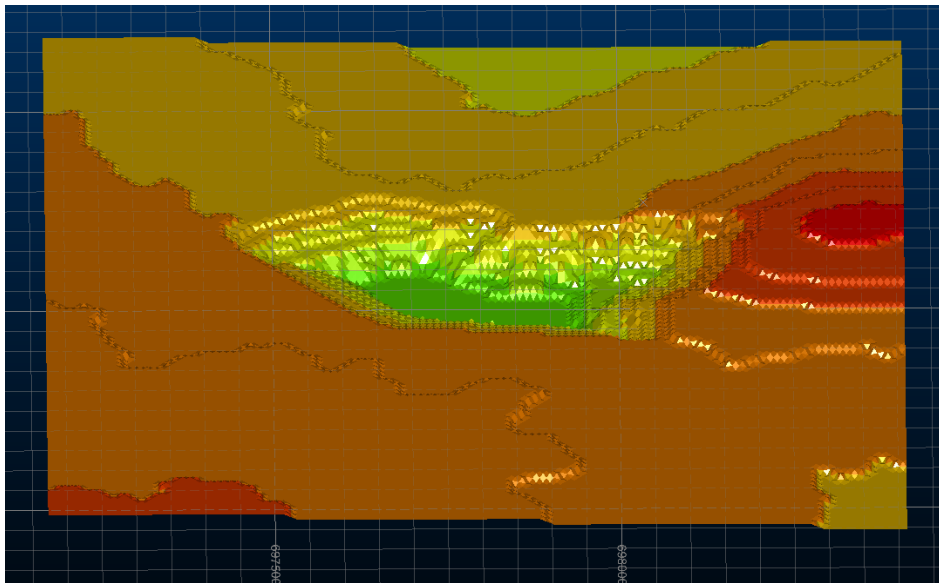


Figure 20. Side view of pushback no. 1 (Optimistic Scenario).

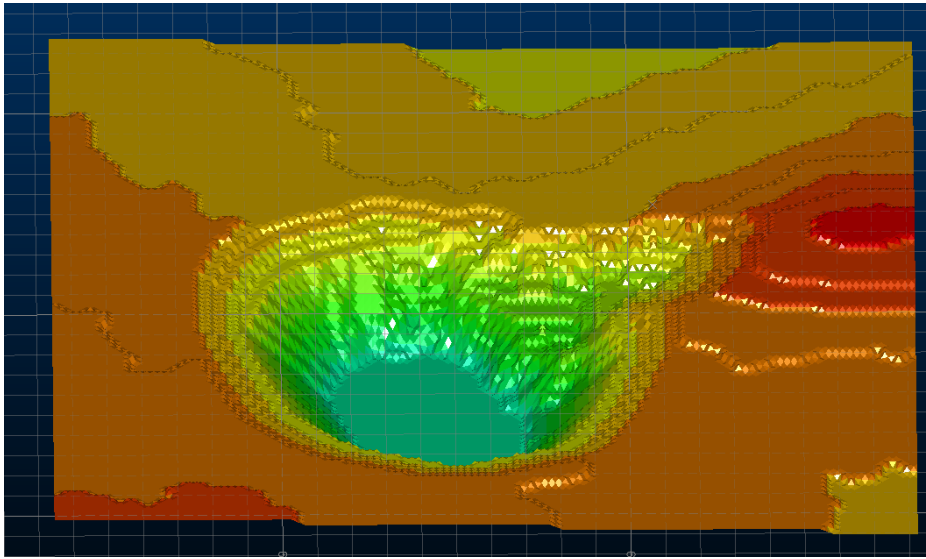


Figure 21. Side view of pushback no. 2 (Optimistic Scenario).

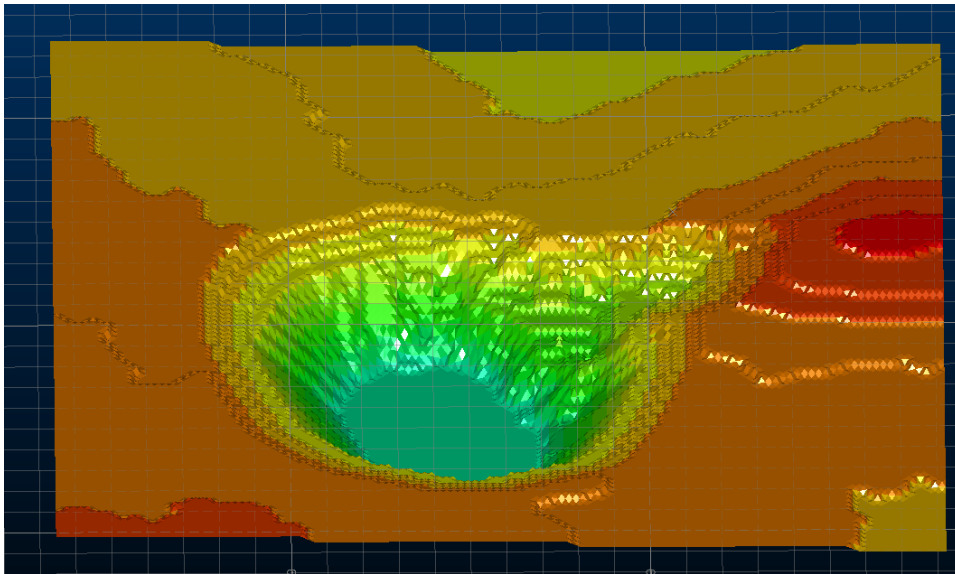


Figure 22. Side view of pushback no. 3 (Optimistic Scenario).

Table 16 provides the tonnage ore, waste and profit for each pushback.

Table 16. Ore, waste, and profit generated within each pushback (Optimistic Scenario).

<i>Pushbacks</i>			
Pushback	ORE	Waste	Profit
1	5,319,600	14,675,500	454,349,329
2	4,995,900	49,569,800	286,557,261
3	3,357,900	7,235,500	292,755,297

Then, the final shape for ultimate pit limit is constructed. The figures below demonstrate the graphical illustrations of the ultimate pit limit of the optimistic scenario.

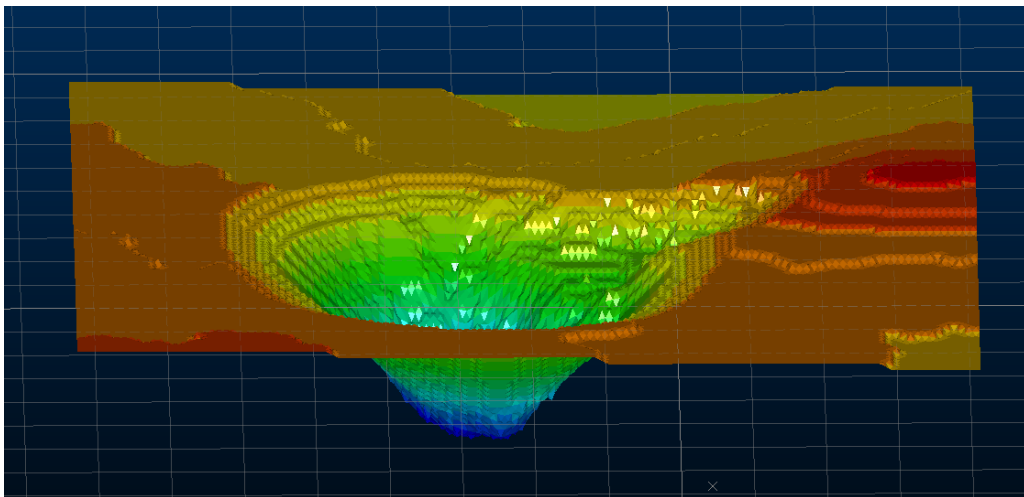


Figure 23. Side view of pit limit (Optimistic Scenario).

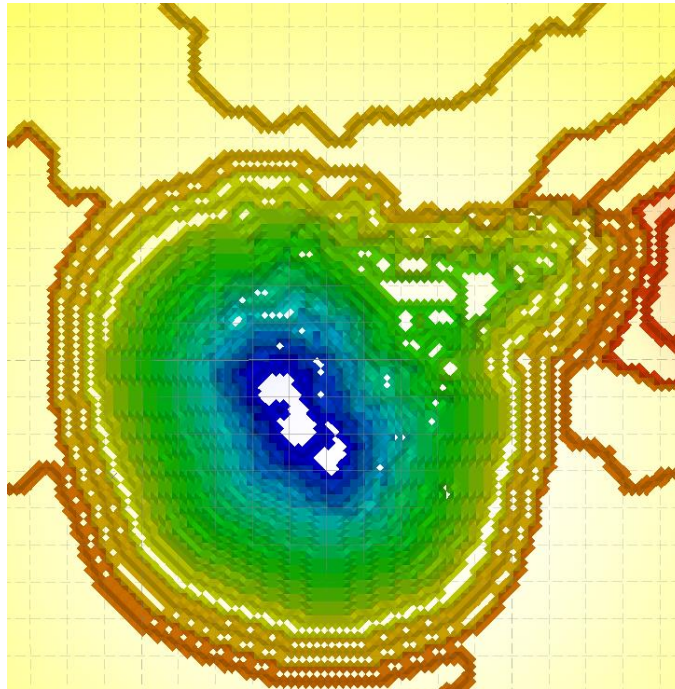


Figure 24. Plan view of pit limit (Optimistic Scenario).

The lifetime of the project is also predicted to be 10 years. Table 17 below shows the results of simulation of 10 years of production – revenue, mining and processing costs for the entire project.

Table 17. Scheduling results by time periods

Cumulative Data																
Year	Rock	Revenue	Processing Cost	Mining Cost	Capital Costs	NPV	ORE	ORE (w)	WEATH	SOIL	FRESH	Au	Cu	Au R	Cu R	Strip
	tonnes	\$	\$	\$	\$	\$	tonnes	tonnes	tonnes	tonnes	tonnes	g	tonnes	g	tonnes	
1	2,005,800	85,805,285	17,390,217	6,548,640	0.0000	58,133,138	588,900	495,300	0.0000	921,600	0.0000	2,624,424	1,140	1,660,846	609,7970	2.4060
2	4,755,000	168,673,255	34,547,799	14,881,440	0.0000	106,434,465	1,158,300	1,010,100	0.0000	2,586,600	0.0000	5,167,839	2,216	3,268,030	1,178	3.1052
3	7,865,700	265,045,073	52,612,716	24,113,040	0.0000	158,575,777	1,747,200	1,524,900	0.0000	4,593,600	0.0000	7,987,975	3,288	5,155,615	1,718	3.5019
4	15,389,500	618,396,915	127,029,045	50,119,760	0.0000	333,958,049	4,038,500	3,728,400	864,600	6,710,400	49,600	18,628,672	7,559	12,037,743	3,951	2.8126
5	46,981,500	967,337,910	208,254,774	144,492,360	0.0000	443,132,265	6,325,800	5,986,500	14,927,000	19,674,000	68,200	29,149,325	12,116	18,793,154	6,422	6.4270
6	61,673,100	1,325,576,683	299,958,477	195,924,540	0.0000	560,940,525	8,700,900	9,114,300	24,087,800	19,674,000	96,100	40,066,689	16,604	25,748,075	8,832	6.0881
7	71,289,500	1,713,369,444	396,917,508	230,980,960	0.0000	685,754,751	11,013,600	12,070,500	28,320,600	19,674,000	210,800	51,397,757	21,085	33,306,634	11,246	5.4729
8	78,765,600	2,109,326,493	504,334,077	259,235,340	0.0000	798,668,547	13,380,900	15,093,000	30,371,000	19,675,800	244,900	62,992,433	25,742	41,016,903	13,759	4.8864
9	84,799,300	2,508,133,039	620,991,111	282,991,640	0.0000	898,201,281	15,728,700	18,298,800	30,841,800	19,675,800	254,200	74,648,318	30,090	48,813,777	16,087	4.3914
10	85,154,200	2,542,151,740	630,803,160	284,411,240	0.0000	906,453,435	15,912,000	18,470,400	30,841,800	19,675,800	254,200	75,622,696	30,384	49,488,135	16,226	4.3516

Table 18 below shows LG phases of the optimistic scenario. The highest cumulative NPV is observed in Pit 88 – 914,612,423 \$.



Table 20. Economic output of the simulation (Optimistic Scenario).

Global Stats													
Cash	Revenue	Minimum	Maximum	Process Cost	Minimum	Maximum	Mining Cost	Minimum	Maximum	Net Value	Ore Value		
	2,917,598,076	115,230	1,867,302	754,206,765	115,167	216,567	3,760,318,420	4,320	15,600	(1,596,927,109)	2,090,149,311		
	Block Count	Mass											
ORE	4,695	18,310,500											
Waste	408,889	1,059,642,500											
Total	413,584	1,077,953,000											
Strip Ratio	57.8708												
ORE Stats													
	Mass	Au	Au Min	Au Max	Cu	Cu Min	Cu Max	Au R	Au R Min	Au R Max	Cu R	Cu R Min	Cu R Max
	tonnes	g	g/tonne	g/tonne	tonnes	Percent	Percent	g	g/tonne	g/tonne	tonnes	Percent	Percent
ORE	18,310,500	86,934,297	0.4566	9.9856	34,835	0.0003%	0.5994%	56,808,429	0.0662	9.3377	18,547	0.0000%	0.4855%
Waste Stats													
ORE (w)	25,654,200												
WEATH	355,102,000												
SOIL	94,024,800												
FRESH	584,861,500												
Total	1,059,642,500												

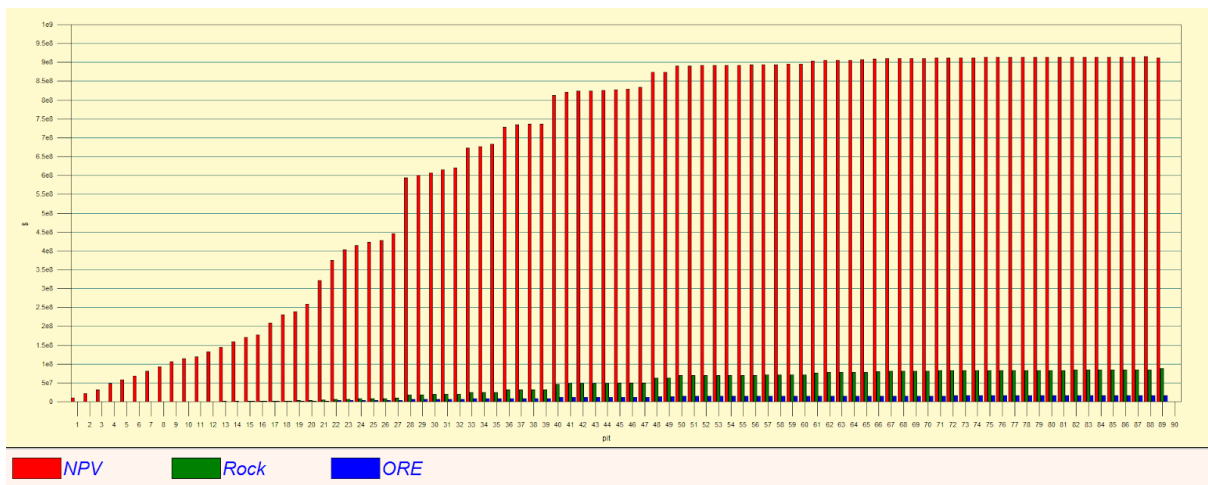


Figure 25. The histogram of NPV, ore and waste tonnage (Optimistic Scenario).

### 4.3 Pessimistic Scenario

Figures 26 - 28 demonstrate the mining pushbacks of the pessimistic scenario. The software provided three pushbacks for the pessimistic scenario.

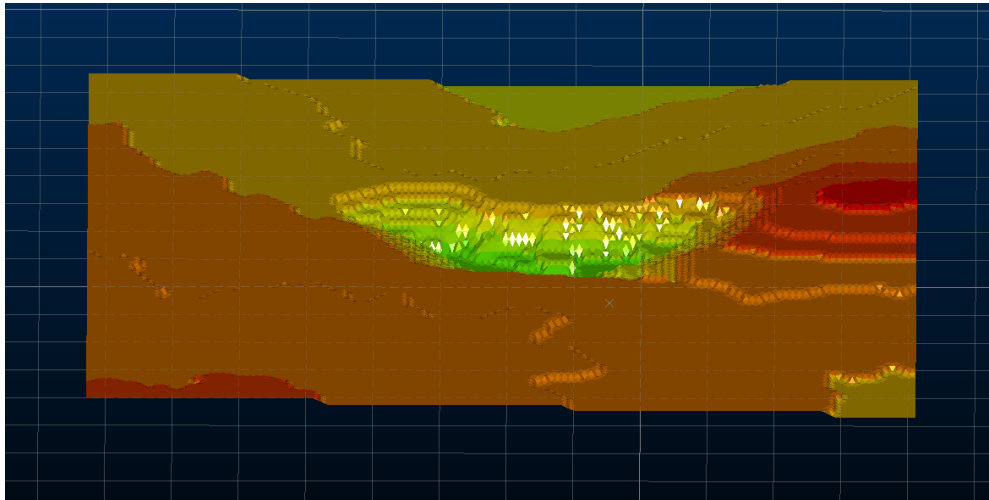


Figure 26. Side view of pushback no. 1 (Pessimistic Scenario).

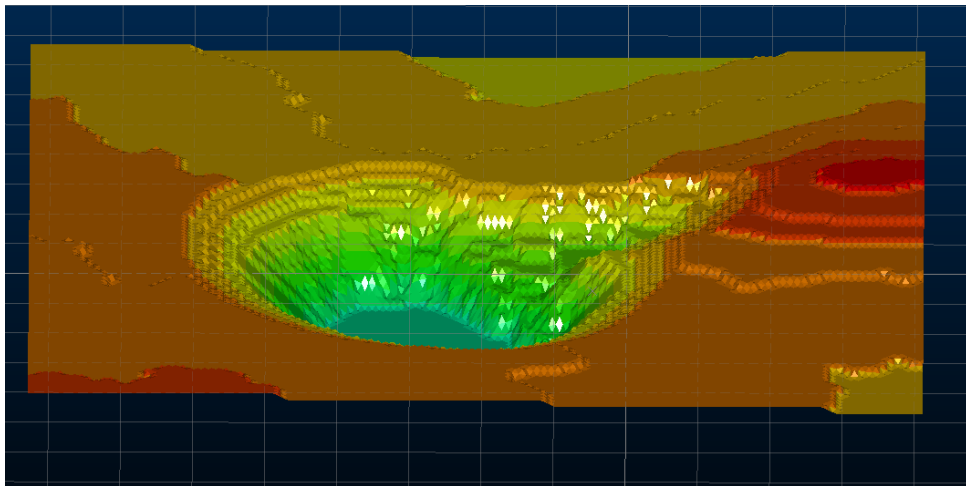


Figure 27. Side view of pushback no. 2 (Pessimistic Scenario).

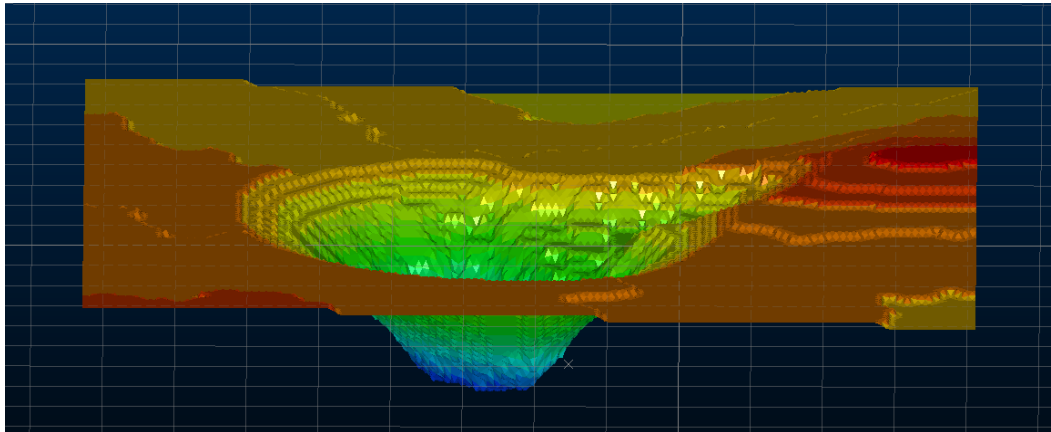


Figure 28. Side view of pushback no. 3 (Pessimistic Scenario).

Table 21 provides the tonnage of ore, waste and profit for each pushback.

Table 21. The tonnage of ore, waste and profit for each pushback (Pessimistic Scenario).

<i>Pushbacks</i>			
Pushback	ORE	Waste	Profit
1	4,071,600	12,505,600	251,596,499
2	3,837,600	42,786,800	77,910,836
3	2,550,600	6,554,000	153,088,150

Then, the final shape for ultimate pit limit is constructed. The figures below demonstrate the graphical illustrations of the ultimate pit limit of the pessimistic scenario.

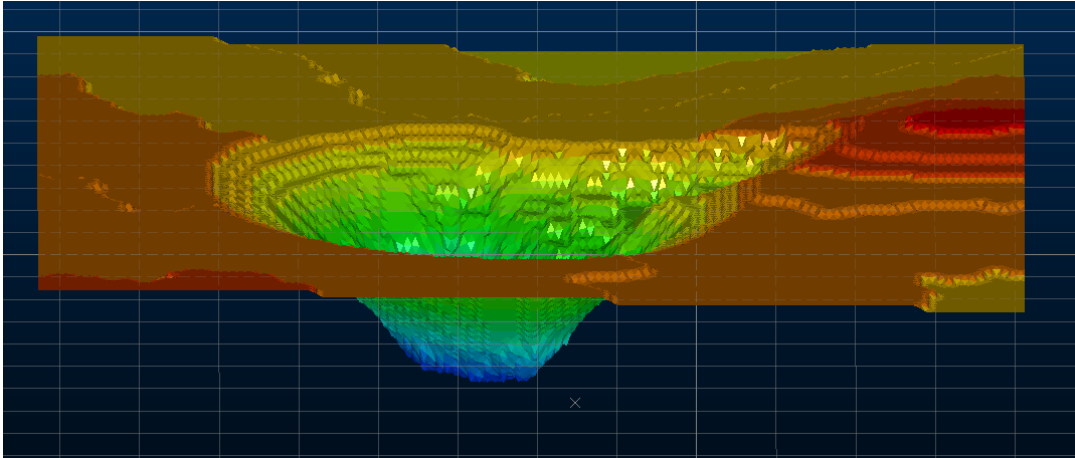


Figure 29. Side view of pit limit (Pessimistic Scenario).

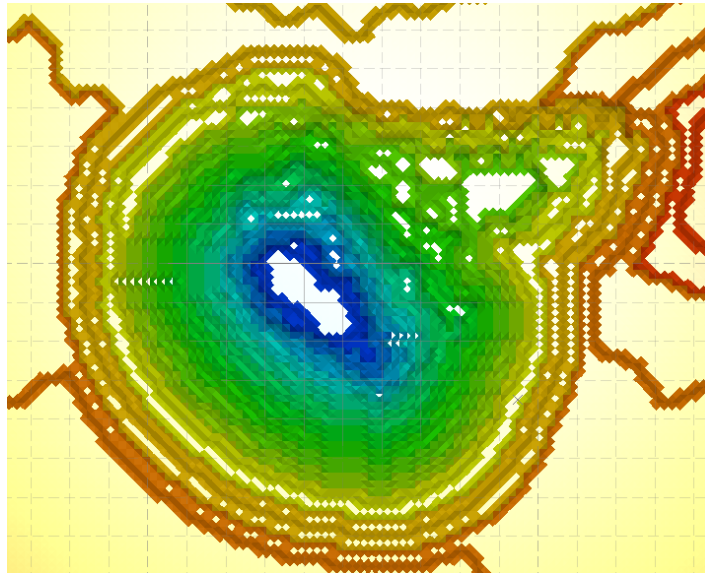


Figure 30. Plan view of pit limit (Pessimistic Scenario).

The lifetime of the project is predicted to be 8 years. Table 22 below shows the results of simulation of 8 years of production – revenue, mining and processing costs for the entire project.



Table 24. The economic cut-off grade of the pessimistic scenario.

Au Economic COG	3.2227	g/tonne
Cu Economic COG	0.8858%	Percent

Finally, the economic results of the pessimistic scenario is shown in Table 20. Moreover, the histogram of the NPV, ore and waste tonnage is shown in Figure

Table 25. Economic output of the simulation (Pessimistic Scenario).

Global Stats													
Cash	Revenue	Minimum	Maximum	Process Cost	Minimum	Maximum	Mining Cost	Minimum	Maximum	Net Value	Ore Value		
	1,721,121,588	178,081	1,244,632	710,122,491	172,731	274,131	5,640,477,630	6,480	23,400	(4,629,478,533)	934,691,697		
Block Count		Mass											
ORE	3,261	12,717,900											
Waste	410,323	1,065,235,100											
Total	413,584	1,077,953,000											
Strip Ratio	83.7587												
ORE Stats													
	Mass	Au	Au Min	Au Max	Cu	Cu Min	Cu Max	Au R	Au R Min	Au R Max	Cu R	Cu R Min	Cu R Max
	tonnes	g	g/tonne	g/tonne	tonnes	Percent	Percent	g	g/tonne	g/tonne	tonnes	Percent	Percent
ORE	12,717,900	71,093,295	2.5947	9.9856	23,726	0.0003%	0.5994%	50,879,464	0.8460	9.3377	12,491	0.0001%	0.4855%
Waste Stats													
ORE (w)	31,246,800												
WEATH	355,102,000												
SOIL	94,024,800												
FRESH	584,861,500												
Total	1,065,235,100												

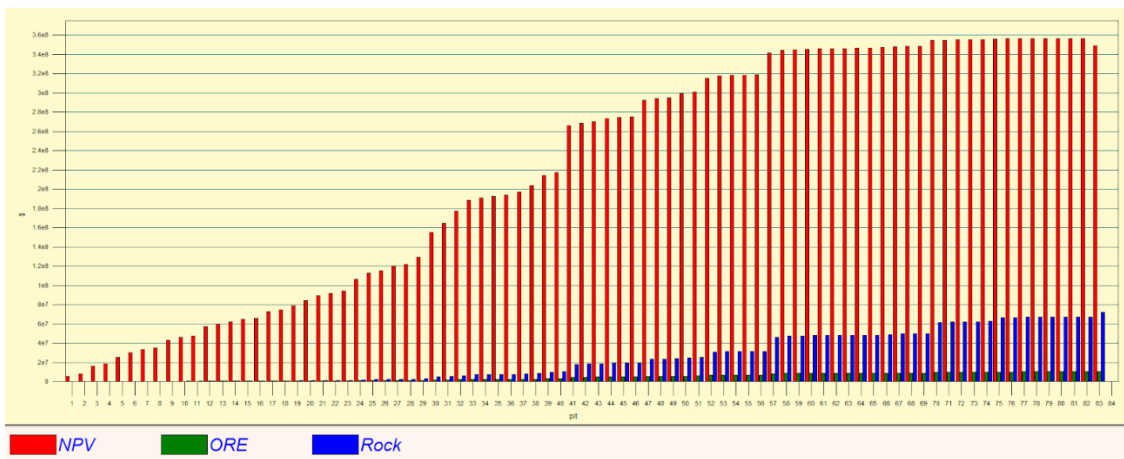


Figure 31. The histogram of NPV, ore and waste tonnage (Pessimistic Scenario).

#### 4.4 Sensitivity Analysis

In the following section, the results of the sensitivity analysis will be provided. The results show how the price variation of gold will affect the economic parameters of the gold-copper open pit mine – Net Present Value (NPV), revenue, and economic cut-off grade. Table 26 present NPV of each price scenario.

Table 26. Sensitivity analysis on Net Present Value.

Sensitivity	Net Present Value (NPV)
20%	\$ 858,642,518.00
10%	\$ 753,939,427.00
-10%	\$ 545,327,291.00
-20%	\$ 438,195,130.00

Figure 32 shows the trend of NPV with regard to ore price fluctuations.

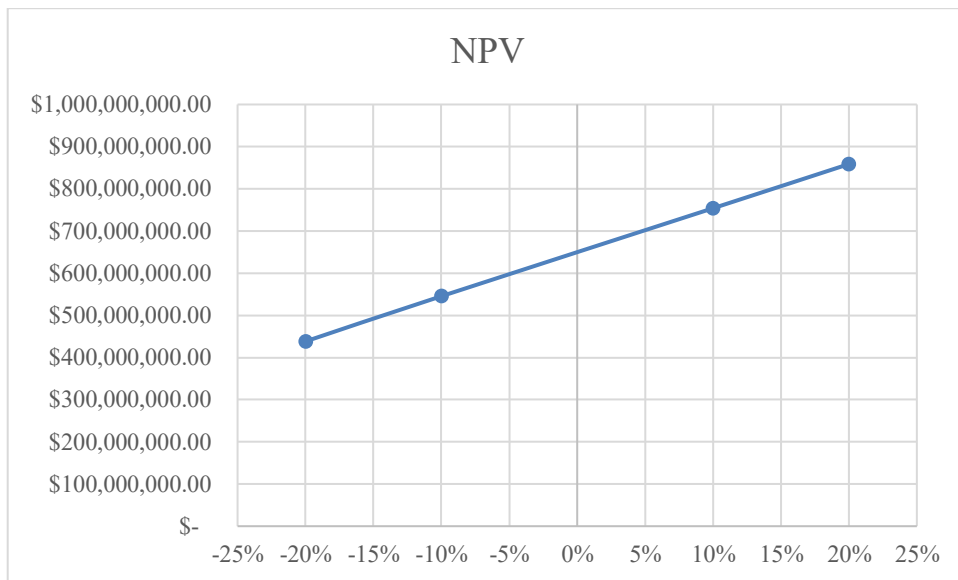


Figure 32. Graph of NPV vs. Price Sensitivities.

Table 27 demonstrates revenue on each price scenario.

Table 27. Sensitivity analysis on revenue.

Sensitivity	Revenue
20%	\$ 2,857,571,149.00
10%	\$ 2,586,694,785.00
-10%	\$ 2,046,707,126.00
-20%	\$ 1,774,977,272.00

Figure 33 shows the trend of revenue with regard to ore price fluctuations.

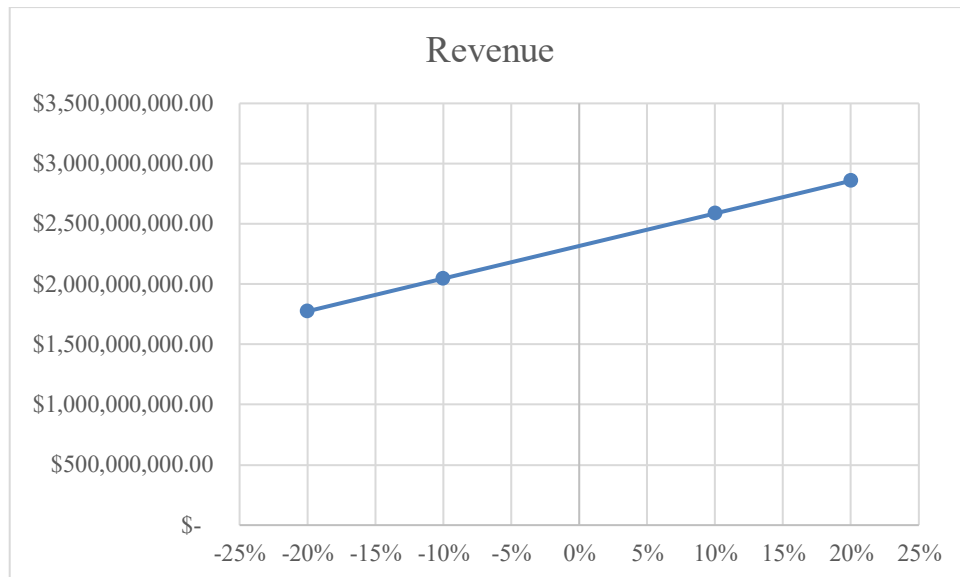


Figure 33. Graph of revenue vs. Price Sensitivities.

Table 28 demonstrates cut-off grade on each price scenario.

Table 28. Sensitivity analysis on cut-off grade.

Sensitivity	Net Present Value (NPV)
20%	\$ 858,642,518.00

10%	\$ 753,939,427.00
-10%	\$ 545,327,291.00
-20%	\$ 438,195,130.00

Figure 34 shows the trend of cut-off grade with regard to ore price fluctuations.

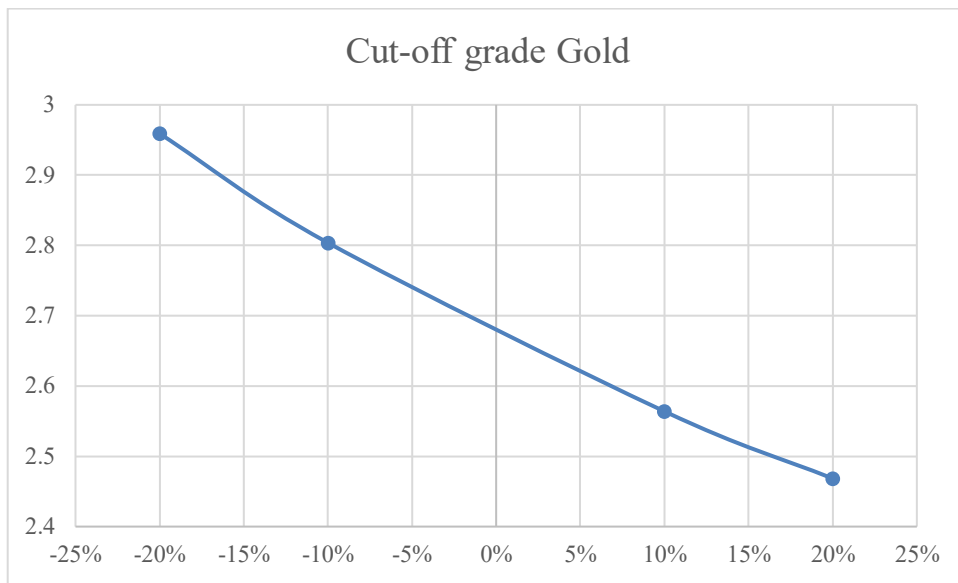


Figure 34. Graph of cut-off grade vs. Price Sensitivities

#### 4. DISCUSSION

In the discussion section, the results of the software simulations will be analyzed and compared. Optimized software simulation provided the experimental results on open-pit mine block sequencing and scheduling with optimistic and pessimistic scenarios. The economic parameters of the base case were given in Table 5. The software provided four mining pushbacks for 10 years of life of mine. The net present value of the project is estimated to be 649,027,644 \$. The cut-off grades for gold and copper are 2.6743 g/t and 0.6481% respectively. The optimistic scenario has a 20% increase in the price of the ores (gold and copper), while

mining and processing costs have decreased by 20% compared to the base case scenario. The simulation results of optimization provide three mining pushbacks for the same 10 years of life of mine. The estimated NPV of the scenario is supposed to be 914,612,423 \$. The cut-off grades for gold and copper are 2.2455 g/t and 0.5324% respectively. Finally, the pessimistic scenario, in contrast, has a 20% decrease in price and a 20% increase in mining and processing costs. The simulation produced three mining pushbacks for 8 years of life of mine. The NPV is expected to be 356,593,171 \$ in Pit no. 82. The cut-off grades are 3.2227 g/t and 0.8858% for gold and copper respectively. It could be observed that all three scenarios have unique results for mine planning optimization. Figures 23 and 28 demonstrate the ultimate pit limits for each scenario and it could be found that pit limits for the pessimistic scenario are lower than the optimistic one. The reason is that mining lower blocks are not likely to be profitable as the revenue will not outweigh the mining and processing costs. Therefore, the ultimate pit limit of the optimistic scenario is greater than the pessimistic scenario.

There are no significant changes in the number of generated pushbacks among the three scenarios. The software provided three pushbacks on average for the projects. The tonnage of waste generated in the three cases has a slight difference. However, the tonnage of ore is significantly higher in the optimistic scenario (Table 16). This could be explained by the fact that despite ore being mined, it does not process further. It is not profitable to send it to the processing plant.

Price fluctuations had a considerable impact on economic cut-off grades for the scenarios. The pessimistic scenario has a higher cut-off grade (3.2227 g/t and 0.8858% for gold and copper respectively) compared to the base and optimistic scenarios. Higher cut-off grades minimize the number of mining blocks as mining cost is increased in the following scenario. As a result, the sequence of extraction is slightly different from the base case. The approach described in this work is limited to a single processing destination. Therefore, cut-off grades for the following project are constant for the entire mining operations in software computation. Figure 34 shows the trend of the cut-off grade of the gold considering price uncertainties. It could be observed that the cut-off grade is inversely proportional to the price. The higher prices for the

ore results in lower cut-off grades and vice versa. Therefore, the mining projects should have flexible cut-off grades for entire life of mine, because the ore price is fluctuating according to the market.

Tables 12, 17, and 22 illustrate the scheduling results of the three scenarios. The software provided 10 years of operation both for the base and optimistic scenarios. While life of mine in the pessimistic scenario is expected to be 8 years. As was mentioned before, mining additional blocks are not as profitable as the optimistic case. Due to a decrease in the price by 20% and an increase in the mining and processing costs by 20%, the overall production years are slightly declined. In the optimistic scenario total mining cost is expected to be 284,411,240 \$, while in the pessimistic scenario it is expected to be 363,940,440 \$. Moreover, it is important to mention that the mining cost of the optimistic scenario is targeted at 10 years, and 8 years for the pessimistic scenario. The same tendency is observed in the processing costs.

Finally, one of the most crucial parameters is the Net Present Value. The NPV is remarkably affected by price changes. The NPV depends on the price of the materials. Thus, increased price enhances the NPV of the project. Figure 32 demonstrates the relationship between these two components. The NPV of the project grows linearly as the price increase. As a result, the highest NPV is found in optimistic scenario - 914,612,423 \$.

The results from Tables 13, 18, and 23 could be considered the important ones in the following thesis paper since it represents the project even in a more detailed way by splitting it into numerous LG phases. These pits are assigned to sequential numbers and provide economic parameters of the blocks. The results showed the highest Net present value is observed in Pit no. 88 in the optimistic scenario (+20% in price) – 914,612,423 \$, while the lowest NPV results were in the pessimistic scenario (-20% in price) - 356,593,171 \$ in Pit no. 82. Indeed, the Lerchs-Grossman method is still treated as the main foundation for open pit mine planning and sequence of extraction.

## 5. CONCLUSIONS AND RECOMMENDATIONS

To sum up, block sequencing simulation results were evaluated and compared with modern block sequencing approaches. With the help of Datamine Studio NPVS and a real-world input model, the block sequencing and mine planning areas were simulated. The global literature review section provided several approaches such as direct block sequencing, Lagrangian relaxation, variable elimination, relaxation of integer programming, etc. Moreover, case studies on mine block sequencing related to real-world mining projects were provided. The above optimization methods were implemented in these cases and the results were favorable as well. The direct block sequencing method was a promising one as periods, parameters, and constraints are fed into the optimization model; however, the complexity of the algorithm does not allow the planners to utilize the following method solely. Utilizing DBS with the conventional Lerchs-Grossman method could slightly improve the net present value of the project. The Lagrangian relaxation could positively affect the algorithm of mixed-integer programming, the approach loosens the constraint function by adding Lagrangian multipliers and implementing them in the software algorithm.

The practical part of the thesis was done throughout the gold-copper open pit mine. Three scenarios (base, optimistic and pessimistic) of optimization considering price fluctuations were analyzed and compared. The results provided the Lerchs-Grossman phases for the optimum sequence of extraction of the mining blocks and the general layout of the project through the ultimate pit limit. Moreover, some distinctions between the three cases were compared and explained. Secondly, the software simulation addressed the economic aspects of the above output of the gold-copper open pit mine. It was found that an increase in product price leads to increased NPV of the project. Whereas, an increase in mining and processing costs negatively affects the economic attractiveness of the project. The appropriate sequence of extraction significantly affects the economic viability of the project considering the highest net present value of the mining blocks. Thus, it could be stated that the mining sequence is a crucial part of open-pit mine planning. The further development of the block sequencing software

computation could lead to more optimized approaches and thus, enhance the economic aspect of the project.

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