Mineral processing plant capacity based on geometallurgical block model scheduling

D B Mazzinghy[1], N Morales[2], A Brickey[3], G Nelis[4], J Ortiz[5] and M J F Souza[6]

1. Professor, Department of Mining Engineering, Universidade Federal de Minas Gerais, Belo Horizonte, Minas Gerais 31.270–901, Brazil. Email: dmazzinghy@demin.ufmg.br
2. Professor, Département des Génies Civil, Géologique et des Mines, Polytechnique Montréal, Montreal QC H3T 1J4, Canada. Email: nelson.morales@polymtl.ca
3. Professor, Mining Engineering and Management Department, South Dakota School of Mines and Technology, Rapid City SD 57701, USA. Email: andrea.brickey@sdsmt.edu
4. Professor, Departamento de Ingeniería de Minas, Metalúrgica yMateriales, Universidad Técnica Federico Santa María, Santiago 8940897, Chile. Email: gonzalo.nelis@usm.cl
5. Professor, Camborne School of Mines, University of Exeter, Falmouth, Cornwall TR10 9FE, UK. Email: j.ortiz-cabrera@exeter.ac.uk
6. Professor, Department of Computing, Universidade Federal de Ouro Preto, Ouro Preto, Minas Gerais 35.402–136, Brazil. Email: marcone@iceb.ufop.br

ABSTRACT

The geometallurgy approach seeks to connect different areas, such as geology, mining, processing, finance, and environment, in an integrated workflow to increase the knowledge of the orebody. It has been used successfully to reduce risks in greenfield and brownfield projects. During the development of the greenfield project, the mineral processing plant capacity is usually estimated using a large sample composite by some drill hole intervals from different deposit areas. This sample is often called a 'representative sample', and it is used to perform a pilot plant test to obtain parameters for plant capacity calculation. For example, a greenfield project with 2000 drill hole intervals and chemical composition data may only have 20 comminution tests from composite drill hole intervals. Considering the ore variability, the risk of over or underestimating the plant capacity is high. Nowadays, it is possible to obtain comminution indices during the sample preparation of the drill hole intervals for chemical composition analysis using devices like the Geopyörä Breakage Test (GBT) and Hardness Index Testing (HIT). These devices need a small sample mass, and the tests are done quickly and cheaply. The comminution indices like Impact Breakage Index (*A*b*) and Bond Work Index (*BWI*) can be converted into specific energy (kWh/t), and the plant capacity per period can be estimated from mine scheduling, considering the plant operational time as a constraint. It is common to have approximately 8000 hrs/annum as plant operational time, depending on the equipment availability. Then, it is possible to find the best time in the Life-of-mine (LOM) to expand the plant to maintain the concentrate quality and production, for example. The methodology presented here can estimate the plant capacity according to the geometallurgical block model scheduling, avoiding future bottlenecks and supporting investment decision-making.

INTRODUCTION

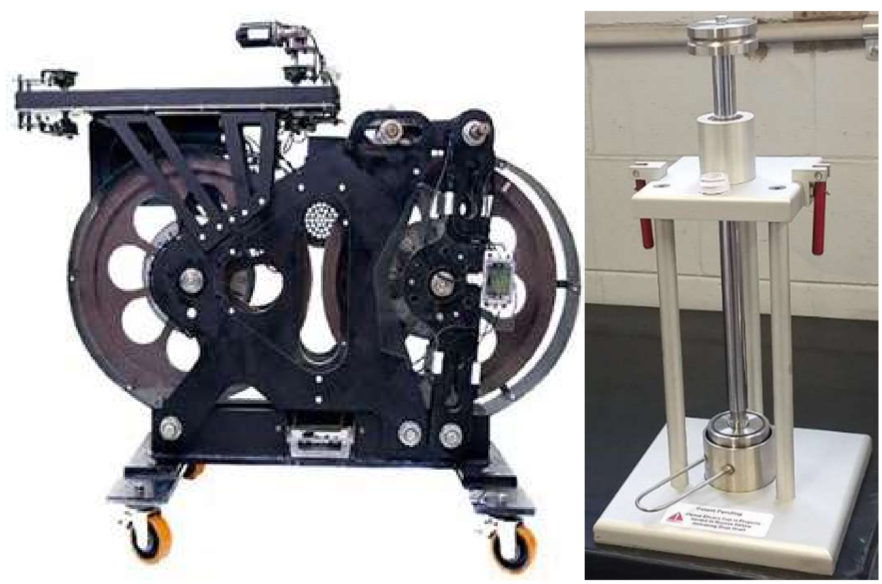
The mining industry is currently changing due to declining ore grades, resulting in a significant increase in the volume of run-of-mine (ROM) to be processed to achieve the same product quantity specifications. It is necessary to understand the orebody deeply to avoid some problems, such as reduced production capacity and out-of-specification products during the life-of-mine (LOM). The heterogeneous nature of orebodies and the variability in physical and chemical properties of the lithologies make mining operations very challenging, and the geometallurgy approach provides a more integrative process. Geometallurgy is an interdisciplinary approach that plays a pivotal role in any project's evaluation or proposed mining operation, and it focuses on spatially characterising the different material types or domains within a deposit, considering their impact on processing, mining performance, and environmental and closure aspects (Global Mining Guidelines Group (GMG), 2025). The geology information from drill holes and the bench metallurgical test results from these drill cores can be used to predict the mineral processing plant performance; also, mine planning can be performed to maximise the net present value (NPV) of the orebody. A challenge during the development of a greenfield project is the determination of the mineral processing plant capacity.

The plant capacity is usually estimated using large sample composites with a defined drill holes interval. This sample is often called a 'representative sample' and it is used to perform a pilot plant test to obtain parameters for plant capacity calculation. It is very common in a greenfield project to have 2000 drill hole intervals with chemical composition data and just only 20 comminution tests from composite drill hole intervals. Considering the ore variability, the risk during the plant capacity estimation is too high, needing more attention to avoid future bottlenecks. For example, consider two blocks with the same grade and same recovery, but with different hardness. The metal per hour produced by each block will be different once the capacity is a function of the specific energy and processing time. Also, the processing cost will vary according to the block hardness with harder blocks requiring more time to be processed. We can conclude from this simple example that the real value of a block cannot be estimated precisely without the specific energy per block (metal per hour). The processing time can modify the mine planning decision-making process and must be considered in the mine schedule optimisation.

The objective of this investigation is to show an open pit mine schedule that incorporates specific energy as a geometallurgical variable block-by-block and how the processing plant capacity can be properly estimated using this approach. The case study developed during this research can be used to illustrate the impact and importance of incorporating geometallurgy into the mine planning process.

OBTAINING COMMINUTION INDICES FROM DRILL HOLES

Currently, it is possible to obtain comminution indices during the sample preparation of the drill hole intervals for chemical composition analysis using geometallurgical devices like the Geopyörä Breakage Test (GBT) and Hardness Index Testing (HIT). These devices need a small sample mass, with tests being cheap and quick. The comminution indices like Impact Breakage Index (*A*b*) and Bond Work Index (*BWI*) can be converted into specific energy (kWh/t) and then converted in processing time (h). Figure 1 presents the GBT (Bueno *et al,* 2024) and the HIT (Bergeron *et al,* 2017) devices.



(a) (b)

FIG 1 – (a) Geopyörä Breakage Test (GBT); and (b) the Hardness Index Testing (HIT).

GBT consists of two counter-rotating wheels that nip and crush the particles with a tightly controlled gap between the rollers. It was designed to obtain comminution indices cheaply and rapidly using a few samples (Bueno *et al,* 2024). HIT is a low impact device developed for rapid rock-hardness determination at a mine site, allowing the determination of rock hardness variability (Varianemil *et al,* 2023). The main goal of GBT and HIT is to provide comminution indices to populate orebody models to increase the knowledge about ore hardness variability and support the mine scheduling and decision-making process.

ESTIMATING THE SPECIFIC ENERGY FROM COMMINUTION INDICES

The SMC Test (Steve Morrell Comminution) is a methodology for estimating the specific energy of any comminution circuit (GMG, 2021). We provide an example showing how the specific energy of a SABC (SAG+Ball+Pebble Crusher) circuit can be estimated with the documented methodology. Figure 2 shows a simplified version of the processing flow sheet of the Batu Hijau mine with an SABC circuit (Varianemil *et al,* 2023).

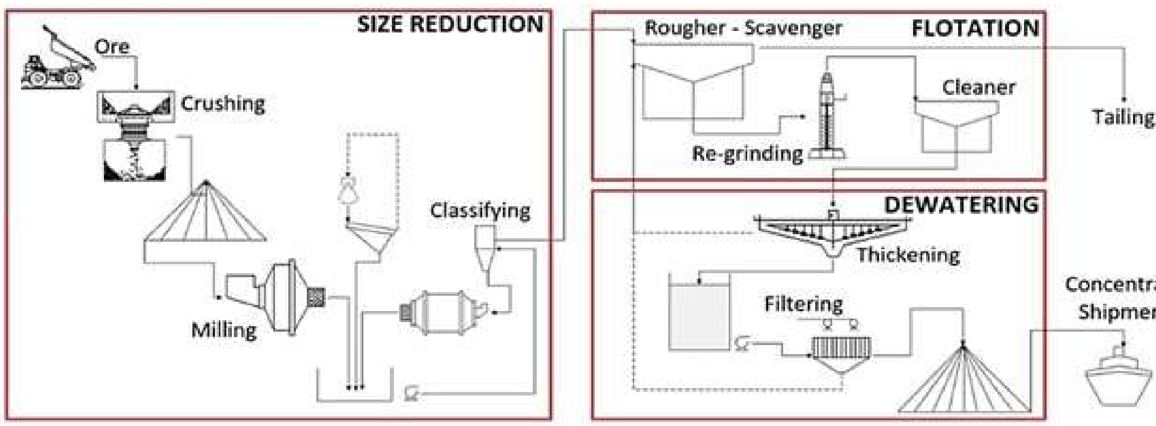


FIG 2 – Batu Hijau process flow sheet showing the SABC circuit (Varianemil *et al,* 2023).

We show the step-by-step calculations necessary to determine the processing time (h) of each block and then populate the block model with the geometallurgical information for use in the mine schedule optimisation process.

Step 1 – Specific energy calculation

The specific energy can be estimated according to Equation 1 (GMG, 2021).

$$E = 4Mia\left(750^{-\left(0{,}295+\frac{750}{10^6}\right)} - F_{80}{}^{-\left(0{,}295+\frac{F_{80}}{10^6}\right)}\right)K_1 + 4Mib\left(P_{80}{}^{-\left(0{,}295+\frac{P_{80}}{10^6 6}\right)} - 750^{-\left(0{,}295+\frac{750}{10^6}\right)}\right) \quad (1)$$

E	specific energy (kWh/t)
Mia	Working index of the coarse ore fraction
F_{80}	80 per cent passing in the feed of the grinding circuit (μm)
K_1	Pebble mill efficiency factor, being 0.95 when there is pebble recirculation and 1 when there is no pebble recirculation
Mib	Work index of the fine ore fraction
P_{80}	80 per cent passing in the product of the grinding circuit (μm)

Step 2 – Estimating *Mia* and *Mib*

The geometallurgical GBT and HIT devices can provide the comminution indices *A*b* and *BWI*. The *A*b* can be converted into *Mia,* and the *BWI* can be converted into *Mib* using Equations 2 and 3 (Doll, 2025):

$$Mia = 379.4\ A * b^{-0.8} \quad (2)$$

$$Screen\ size\ used\ in\ BWI\ \begin{Bmatrix} 300\mu m\ \rightarrow\ Mib =\ 0.60\ BWI^{1.20} \\ 212\mu m\ \rightarrow\ Mib =\ 0.63\ BWI^{1.21} \\ 150\mu m\ \rightarrow\ Mib =\ 0.69\ BWI^{1.22} \\ 106\mu m\ \rightarrow\ Mib =\ 0.71\ BWI^{1.24} \end{Bmatrix} \quad (3)$$

The *BWI* test should be performed using the screen size to produce the P_{80} that will be considered in the mill. Equation 3 shows four screen size models (300 µm, 212 µm, 150 µm, 106 µm). If the P_{80} target in the mill was 150 µm, for example, the screen size used in the BWI test should be the next size above, in this case 212 µm (*BWI*@212 µm).

Step 3 – Estimating *DWi* and F_{80}

The *DWi* can be estimated through the specific gravity SG and the *A*b* using Equation 4 (Doll, 2025):

$$DWi = \frac{100\ SG}{A*b} \tag{4}$$

The F_{80} (mm) of the SAG mill can be estimated considering the close side setting of the primary crusher using Equation 5 (Bailey *et al,* 2009):

$$F_{80} = 0.2\ CSS\ DWi^{0.7} \tag{5}$$

CSS close side setting (mm)

DWi Drop Weight Index (kWh/m^3)

Step 4 – Estimating the plant throughput

The circuit throughput can be calculated knowing the power available and the specific energy through Equation 6:

$$T = \frac{P}{E} \tag{6}$$

T is the throughput (t/h)

P is the mill power available (kW)

E is the specific energy (kWh/t)

Step 5 – Estimating the processing time

The processing time *PT* (h) can be calculated knowing block mass M_B (t) and the throughput *T* (t/h) using Equation 7:

$$PT = \frac{M_B}{T} \tag{7}$$

Step 6 – Estimating the plant availability time

The total time of the plant operation per annum can be calculated as 7884 hrs, considering 365 days per annum, 24 hrs per day, and 90 per cent operational yield, for example.

OPEN PIT MINE SCHEDULING PROBLEM

We present the two main methodologies of formulating the mine planning problem that were proposed in the 1960s; one presented by Lerchs and Grossmann (1965) and the other by Johnson (1968). However, due to the limitation of hardware and software at the time, only the Lerchs and Grossmann (LG) approach was tractable resulting in its development and becoming the industry standard for many decades. LG model finds the ultimate pit limit that provides the maximum undiscounted revenue at time zero. It can be used to produce nested pits obtained by changing the value of the blocks by applying a revenue factor. Then, the user must find the best pits containing the masses and grades for each period. Nested pit approach serves as an indication of where the highest value sectors are located inside the pit, and therefore, they are used as a guide to define a production schedule. However, there is no guarantee that the production schedule derived from the nested pits is optimal, especially when additional constraints are considered (blending, capacity etc). Nowadays, the pseudoflow algorithm (Hochbaum, 2001) is preferred because it is faster than the LG algorithm. Johnson approach has been proposed to tackle this issue and consists of scheduling the blocks using mixed integer linear programming (MILP). It can obtain an optimum solution, but this method is limited to solving real instances of the problem, which may involve several million blocks. The mine scheduling problem is NP-hard (Deutsch, Dağdelen and Johnson*,* 2022), and no algorithms solve this problem in polynomial time. Bienstock and Zuckerberg (2009) proposed a new algorithm that, through linear programming relaxations, finds high-quality solutions in instances with millions of variables and constraints of the mine scheduling problem. The BZ algorithm works in multiple steps to produce a mine schedule:

1. Aggregate block scheduling decisions in a column generation procedure using pseudoflow algorithm and then run a very small and fast linear programming optimisation.
2. This result is used for the subsequent round of column generation and this procedure is repeated until reaching the bound.
3. A very fast heuristic is used to give a complete schedule that is close to optimum.
4. Use the bound from BZ to speed up a MILP solver running the full problem.
5. Uses the branch-and-cut to iteratively use BZ to reach the optimum solution (Letelier *et al,* 2020; Minemax, 2025).

Direct block scheduling

In this paper, we will use the direct block scheduling concept to solve the open pit mine scheduling problem. In the literature this kind of problem is known as the Precedence Constrained Production Scheduling Problem (PCPSP) (Espinoza *et al,* 2012). In PCPSP, the economic value for a block can be calculated according to its destination, for example, a processing plant or waste dump, using Equations 8 and 9:

$$Process = M_B\ g\ r\ (S_P - S_c) - M_B(C_P + C_M) \tag{8}$$

$$Waste = \ -M_B\ C_M \tag{9}$$

M_B	block mass (t)
g	grade
r	recovery
S_p	selling price ($/t)
S_c	selling cost ($/t)
C_p	processing costs
C_M	mining costs

The optimisation algorithm chooses the best destination for each block based on its value. In this approach, it is not necessary to define cut-off grades or determine before the optimisation if a block is flagged as ore or waste.

We used MiningMath (MM) software in our case study, and the formulation presented here is the one MM used (MiningMath, 2025). Figure 3 presents the simplified flow chart of the MM algorithm.

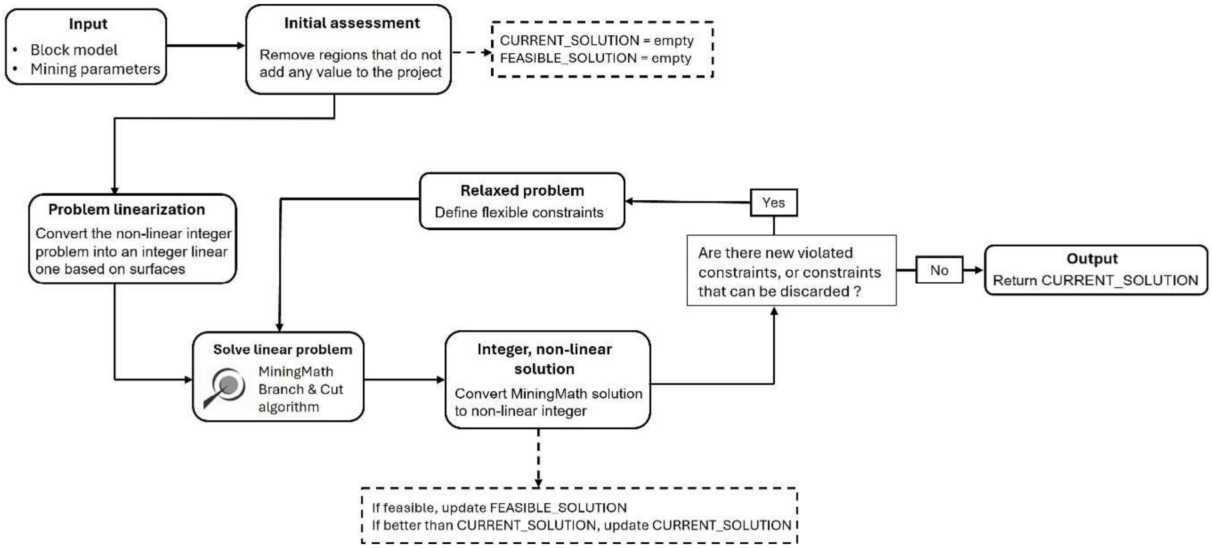


FIG 3 – Simplified flow chart of MiningMath algorithm (MiningMath, 2025).

The first step of the optimisation algorithm is to remove regions that do not add any value to the project, as shown in Figure 4.

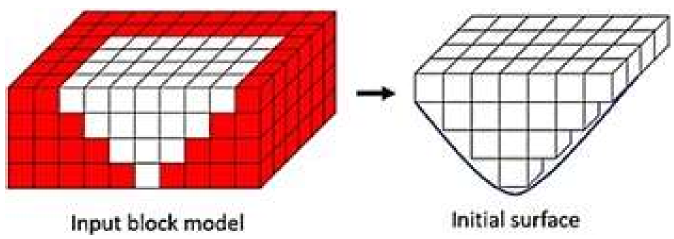


FIG 4 – Removing regions that do not add any value to the project (MiningMath, 2025).

The second step of the optimisation algorithm is converting the non-linear integer problem into a linear one based on surfaces (geometry mine constraints), as shown in Figure 5. BW is the bottom width, MW is the mining width, and ADV is the vertical rate of advance.

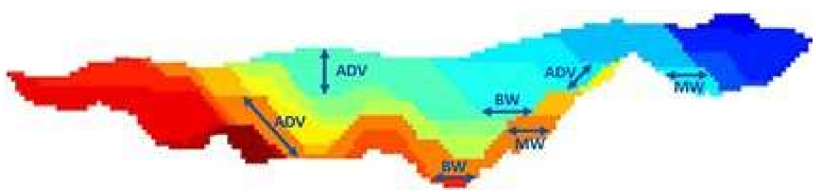


FIG 5 – Example solution with geometric constraints (MiningMath, 2025).

The third step of the optimisation algorithm is converting the linear solution to an integer solution using the branch-and-cut algorithm. This algorithm is more efficient than the branch-and-bound algorithm contained in standard MILP solvers, and it was also fine-tuned for this specific optimisation problem.

Common notation

S number of simulated orebody models considered

s simulation index, $s = 1,.,S$

D number of destinations

d destination index, $d = 1,.,D$

Z number of levels in the orebody model

z level index, $z = 1,.,Z$

T number of periods over which the orebody is being scheduled and also defines the number of surfaces considered

t period index, $t = 1,.,T$

M number of cells in each surface, where $M = x \times y$ represents the number of mining blocks in x and y dimensions

c cell index, $c = 1, \ldots, M$

G number of unique destination groups defined. Each group might contain 1, all, or any combination of destinations

g group index, $g = 1, \ldots, G$

Objective function

The objective function is the sum of the economic value of blocks mined per period, destination, and simulation. It uses the average result divided by the number of simulations and subtracts the penalties for certain violated restrictions associated with some user-defined parameters (Equation 10):

$$max \; \frac{1}{S} \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{c=1}^{M} \sum_{z=1}^{Z} \sum_{d=1}^{D} \left(V_{c,t,d,s}^{z} x_{c,t,d}^{z} \right) - p$$
$$c = 1, \ldots, M, \quad t = 1, \ldots, T, \quad z = 1, \ldots, Z, \quad d = 1, \ldots, D$$
$$x_{c,t,d}^{z} \in \{0,1\} \tag{10}$$

$V_{c,t,d,s}^{z}$ cumulative discounted economic value of block (c,z) in simulation s, period t and destination d

$x_{c,t,d}^{z}$ simulation-independent binary variable that assumes 1 if block (c,z) is being mined in period t and sent to destination d, and 0 otherwise

The penalties can be calculated using Equation 11:

$$p = \sum_{t=1}^{T} \sum_{g=1}^{G} \left(\overline{\alpha_{t,g}} \left(\sum_{s=1}^{S} \overline{f_{t,g,s}} \right) + \underline{\alpha_{t,g}} \left(\sum_{s=1}^{S} \underline{f_{t,g,s}} \right) + \overline{\beta_{t,g}} \left(\sum_{s=1}^{S} \overline{j_{t,g,s}} \right) + \underline{\beta_{t,g}} \left(\sum_{s=1}^{S} \underline{j_{t,g,s}} \right) \right) \tag{11}$$

$\overline{f_{t,g,s}}, \underline{f_{t,g,s}}$ continuous variables to penalise sum constraints violated for each period, group of destinations, and simulation. One pair of variables is necessary for each quantifiable parameter modelled block by block whose sum is being constrained. An example would be variables used to control fleet hours spent in different periods or processing time in the plant, groups of destinations, and simulations.

$\overline{j_{t,g,s}}, \underline{j_{t,g,s}}$ continuous variables to penalise average constraints violated for each period, destination, and simulation. One pair of variables is necessary for each quantifiable parameter modelled block by block whose average is being constrained. An example would be variables used to control the average grade of blocks mined in different periods, destination groups, and simulations.

$\overline{\alpha_{t,g}}, \underline{\alpha_{t,g}}$ user-defined weights for variables $\overline{f_{t,g,s}}, \underline{f_{t,g,s}}$ with the same destination group g and period t. The value used is 1 000 000. It can be changed using advanced configuration.

$\overline{\beta_{t,g}}, \underline{\beta_{t,g}}$ user-defined weights for variables with the same destination d and period t. The value used is 1 000 000. It can be changed using advanced configuration.

Surface constraints

Figure 6 shows two surfaces (blue and yellow): a) not crossing each other and respecting the constraint; b) crossing each other and not respecting the constraint.

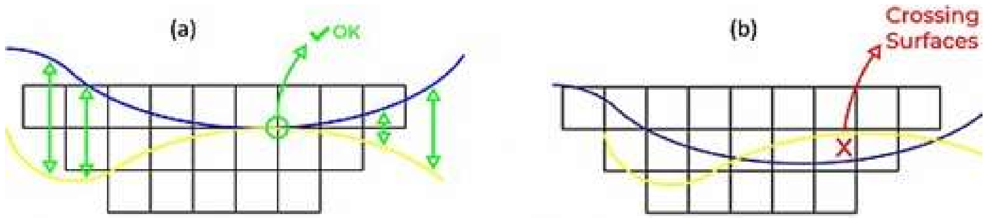


FIG 6 – Surface constraint concept (MiningMath, 2025).

Equation 12 shows the surface constraint:

$$e_{c,t-1} - e_{c,t} \geq 0,$$
$$c = 1, \dots, M, \quad t = 2, \dots, T \qquad (12)$$
$$e_{c,t} \in R, \quad t = 1, \dots, T, \quad c = 1, \dots, M$$

$e_{c,t}$ simulation-independent continuous variables associated with each cell c (set of blocks) for each period t, representing cell elevations

Slope constraints

Adjacent elevations on a single surface need to respect a maximum difference. This maximum value will change based on their adjacent direction: x, y, or diagonally (Equations 13, 14, 15):

$$e_{c,t} - e_{x,t} \geq H_x,$$
$$c = 1, \dots, M, \quad t = 1, \dots, T, \quad x \in X_c \qquad (13)$$

$$e_{c,t} - e_{y,t} \geq H_y,$$
$$c = 1, \dots, M, \quad t = 1, \dots, T, \quad y \in Y_c \qquad (14)$$

$$e_{c,t} - e_{d,t} \geq H_d,$$
$$c = 1, \dots, M, \quad t = 1, \dots, T, \quad d \in D_c \qquad (15)$$

H_x, H_y, H_d maximum difference in elevation for adjacent cells in x, y, and diagonal directions

X_c, Y_c, D_c equivalent to H_x, H_y, H_d $concept$, the sets of adjacent cells, laterally in x, in y, and diagonally, for a given cell c, respectively

Figure 7 shows the adjacent elevations.

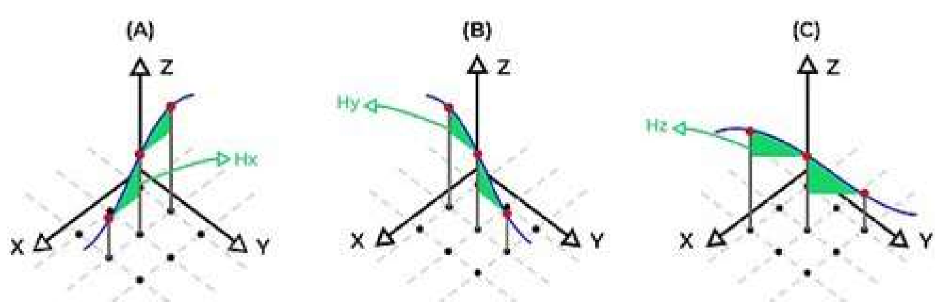


FIG 7 – Adjacent elevations (MiningMath, 2025).

Link constraints

The surfaces define when blocks will be mined. For example, blocks between surfaces associated with period 1 and 2, will be mined in period two. A block is between two surfaces if its centroid is between the two surfaces (Equations 16 and 17):

$$E_c^z \times \sum_{d=1}^{D} x_{c,1,d}^z \geq e_{c,1}, \qquad c = 1, \dots, M, \quad z = 1, \dots, Z \tag{16}$$

E_c^z elevation of the centroid for a given block (c, z)

$$e_{c,t-1} \geq E_c^z \times \sum_{d=1}^{D} x_{c,t,d}^z \geq e_{c,t}, \qquad c = 1, \dots, M, \quad t = 2, \dots, T, \quad z = 1, \dots, Z \tag{17}$$

Figure 8 shows the surfaces between two consecutive periods.

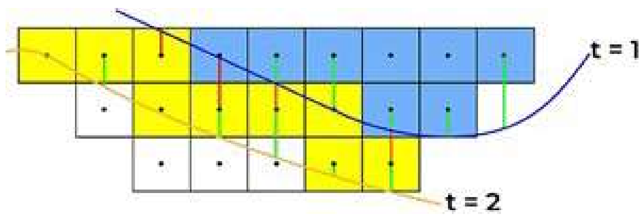


FIG 8 – Surfaces between two consecutive periods (MiningMath, 2025).

Destination constraints

Each mined block can only be sent to one destination (Equation 18):

$$\sum_{d=1}^{D} x_{c,t,d}^z = 1, \qquad c = 1, \dots, M, \quad t = 1, \dots, T, \quad z = 1, \dots, Z \tag{18}$$

Mining constraints

For each period and destination group, there is an upper and lower limit of total tonnage to be extracted. Destination groups might be formed by any unique combination of destinations, with 1, many, or all. The sum of the tonnage of mined blocks sent to the same group of destinations in the same period must respect these limits (Equation 19):

$$\sum_{c=1}^{M} \sum_{z=1}^{Z} \sum_{d \in g} T_c^z x_{c,t,d}^z \leq \overline{T_{t,g}}, \qquad t = 1, \dots, T, \quad g = 1, \dots, G \tag{19}$$

T_c^z tonnage for a given block (c, z)

$\overline{T_{t,g}}$ upper limits in total tonnage to be extracted during period t and destinations in group g

Sum constraints

It is possible to define a certain parameter (ie fleet hours spent, or processing time spent) associated with each mined block to control its sum. The sum of the values of this parameter associated with each mined block must respect lower and upper bounds for each period, destination groups (optional), and simulation (individually or on average). Destination groups might be formed by any unique combination of destinations, with 1, many, or all (Equation 20):

$$\underline{F_{t,g,s}} \le \sum_{c=1}^{M} \sum_{z=1}^{Z} \sum_{d \in g} F_{c,d,s}^{z} x_{c,t,d}^{z} + \underline{f_{t,g,s}} - \overline{f_{t,g,s}} \le \overline{F_{t,g,s}},$$
$$t = 1, \dots, T, \; g = 1, \dots, G, \; s = 1, \dots, S \tag{20}$$
$$\overline{f_{t,g,s}}, \underline{f_{t,g,s}} \in \mathbb{R}_{\ge 0}, \quad t = 1, \dots, T, \quad s = 1, \dots, S, \quad d = 1, \dots, D$$

$\underline{F_{t,g,s}}, \overline{F_{t,g,s}}$ lower and upper limits, respectively, in the sum of user-defined parameters to be respected in the period t, destination group g, and simulation s

$F_{c,d,s}^{z}$ the value of user-defined parameter related to a given block (c, z) in destination d and simulation s

Average constraints

It is possible to define a certain parameter (ie grade) associated with each mined block to be controlled on average. This average is weighted by the block's tonnage and by an optional user-defined weight. It must respect lower and upper bounds for each period, destination group (optional), and simulation (individually or on average). Destination groups might be formed by any unique combination of destinations, with 1, many, or all (Equation 21):

$$\underline{J_{t,g,s}} \le \frac{\sum_{c=1}^{M} \sum_{z=1}^{Z} \sum_{d \in g} P_{c,t,d,s}^{z} T_{c}^{z} J_{c,s,d}^{z} x_{c,t,d}^{z}}{\sum_{c=1}^{M} \sum_{z=1}^{Z} \sum_{d \in g} P_{c,t,d,s}^{z} T_{c}^{z}} + \underline{j_{t,g,s}} - \overline{j_{t,g,s}} \le \overline{J_{t,g,s}},$$
$$t = 1, \dots, T, \quad g = 1, \dots, G, \quad s = 1, \dots, S \tag{21}$$
$$\overline{j_{t,g,s}}, \underline{j_{t,g,s}} \in \mathbb{R}_{\ge 0}, \quad t = 1, \dots, T, \quad s = 1, \dots, S, \quad d = 1, \dots, D$$

$\underline{J_{t,g,s}}, \overline{J_{t,g,s}}$ lower and upper limits, respectively, for the average value of the user-defined parameter to be respected in the period t, simulation s, and destination group g

T_{c}^{z} tonnage for a given block (c, z)

$J_{c,s,d}^{z}$ the value of the user-defined parameter of the block (c, z) sent to a destination d in the simulation s

$P_{c,t,d,s}^{z}$ user-defined weight for a block (c, z) in the period t, destination d, and simulation s

Geometric constraints

Surfaces should respect geometric parameters defined by the user, such as minimum bottom width, minimum mining width, minimum mining length, and maximum vertical rate of advance. It is a proprietary constraint not disclosed, and the intuitive idea is show in Equation 22:

$$Geometric\ (e_{c,t}) \le geometric\ restriction,$$
$$c = 1, \dots, M, \quad t = 1, \dots, T, \tag{22}$$

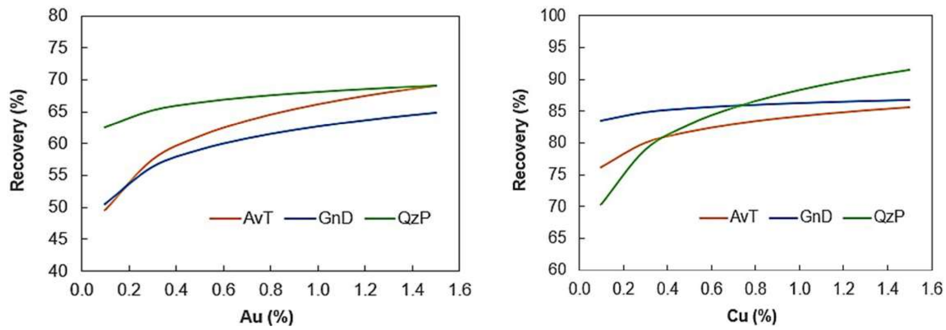
EXPERIMENTS

We used the Marvin block model, which is available for download on the MineLib website (<https://mansci-web.uai.cl/minelib/>). This is a synthetic data set that represents a gold and copper mine (MineLib, 2025).

Table 1 and Figure 9 show the synthetic geometallurgical recovery models for Au and Cu. The main lithologies considered are AvT, GnD, and QzP.

TABLE 1
Geometallurgical models for Au and Cu recoveries.

Lithology	Rec. Au (%)	Rec. Cu (%)
AvT	7.2 ln (Au) + 66.2	3.5 ln (Cu) + 84.2
GnD	5.3 ln (Au) + 62.7	1.2 ln (Cu) + 86.2
QzP	2.4 ln (Au) + 68.1	7.8 ln (Cu) + 88.3



(a) (b)

FIG 9 – Geometallurgical recovery models for: (a) Au; and (b) Cu.

Figure 10 shows some variables for the Marvin data set. The Au and Cu grades were original ones from MineLib. Recoveries were calculated through synthetic geometallurgical models using Au and Cu grades as inputs, as presented in Table 1. The comminution indices *A*b* and *BWI* were estimated based on real gold and copper mines and imputed into the Marvin data set as synthetic data.

The *A*b* and *BWI* were converted to *Mia* and *Mib* using Equations 2 and 3. The *DWi* was estimated using Equation 4. The F_{80} parameter value was estimated using Equation 5, considering the close side setting of the gyratory primary crusher as 150 mm. To calculate the specific energy values of each block, we estimated the F_{80}. We considered *K1* equal to 0.95 (pebble crusher present) and a P_{80} equal to 150 µm. The throughput (t/h) and processing time (h) were calculated according to Equations 6 and 7, respectively. We considered the mill circuit power available as 28 000 kW.

Table 2 presents the economic parameters considered in this investigation. The values used in the Marvin data set were updated with currently approximated values for Au and Cu mines.

TABLE 2
Economic parameters.

Parameters	Values
Selling Price Au (US$/g)	85.00
Selling Cost Au (US$/g)	1.50
Selling Price Cu (US$/t)	8900.00
Selling Cost Cu (US$/t)	3100.00
Processing Cost ($/t)	10.00
Mining Cost ($/t)	4.00
Discount rate (%)	12%

We considered 20 Mt/annum as the maximum capacity for the plant processing and 60 Mt/annum as the maximum capacity for mine. Considering a processing cost equal to 10 US$/t, and if 40 per cent of this value is the fixed cost of the plant and the other 60 per cent corresponds to the milling stage (SAG and Ball mills), we can have the milling cost vary depending on the ore hardness of each block.

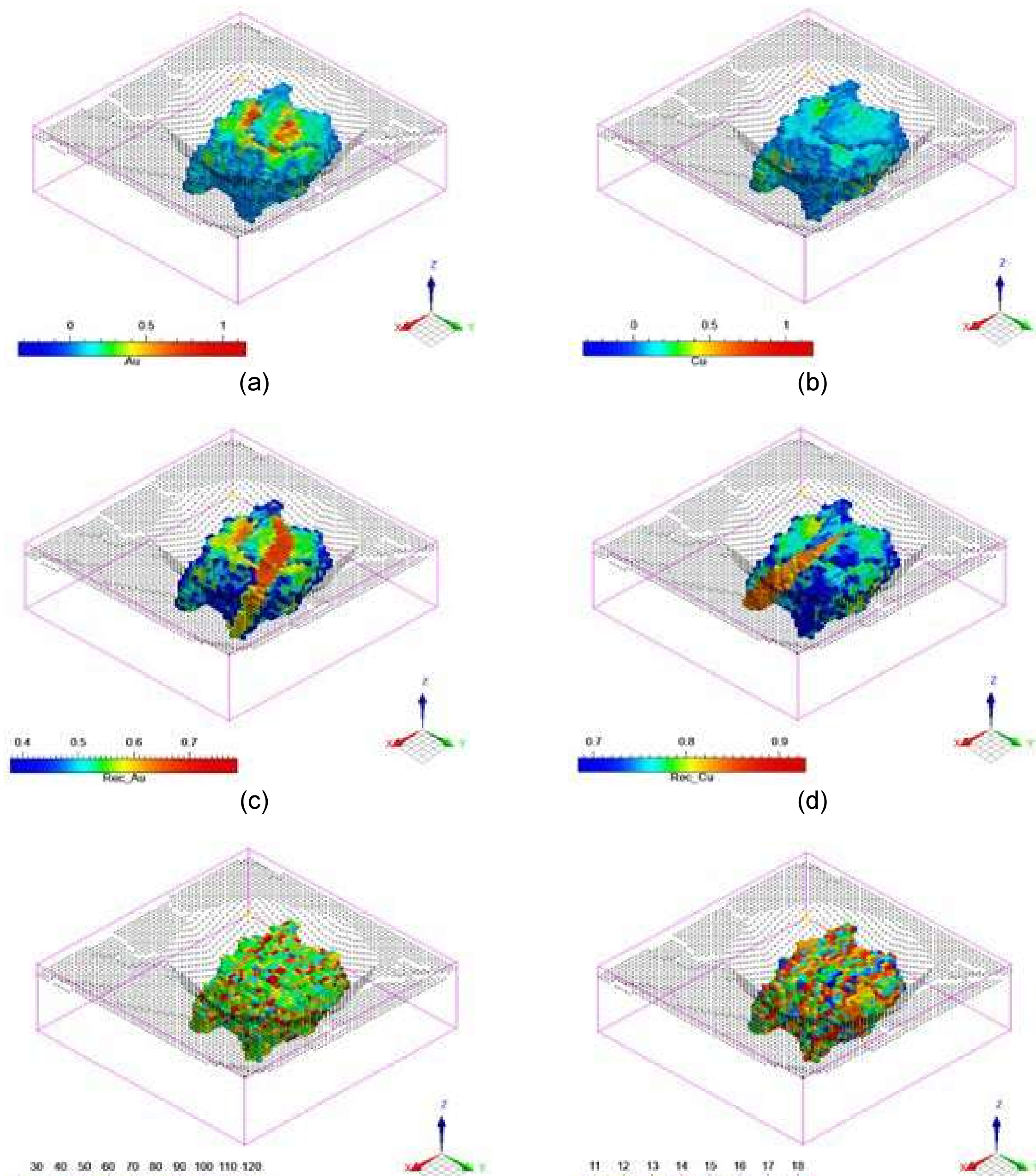


FIG 10 – Marvin data set: (a) Au; (b) Cu; (c) Rec_Au; (d) Rec_Cu; (e) *A*b*; (f) *BWI*.

We produced two scenarios, the first called Marvin and the second called MarvinGeomet. The Marvin scenario considered a fixed processing cost equal 10 US$/t with a consistent specific energy and processing time assigned to all blocks as a base case. The MarvinGeomet scenario considered a variable processing cost according to the ore hardness of each block, and consequently, each block has a different processing time. The maximum processing time considered was 7884 hrs/annum. We compared the processing time of each scenario, even though the processing time of the Marvin scenario was not a constraint in the optimisation. The geometric parameters were the same for both scenarios, minimum mining width equal 60 m, minimum bottom width equal 90 m and maximum vertical rate of advance equal 90 m.

RESULTS AND DISCUSSIONS

The mine scheduling was performed using a Dell Inspiron laptop with an Intel® Core™ i7–10510U CPU@1.80GHz processor, 16 GB of RAM, and a Windows 10 operating system (64-bit). The optimisation time for the two scenarios was less than three mins.

Figure 11 presents the processing and mine capacities, processing time, and net present value for Marvin and MarvinGeomet.

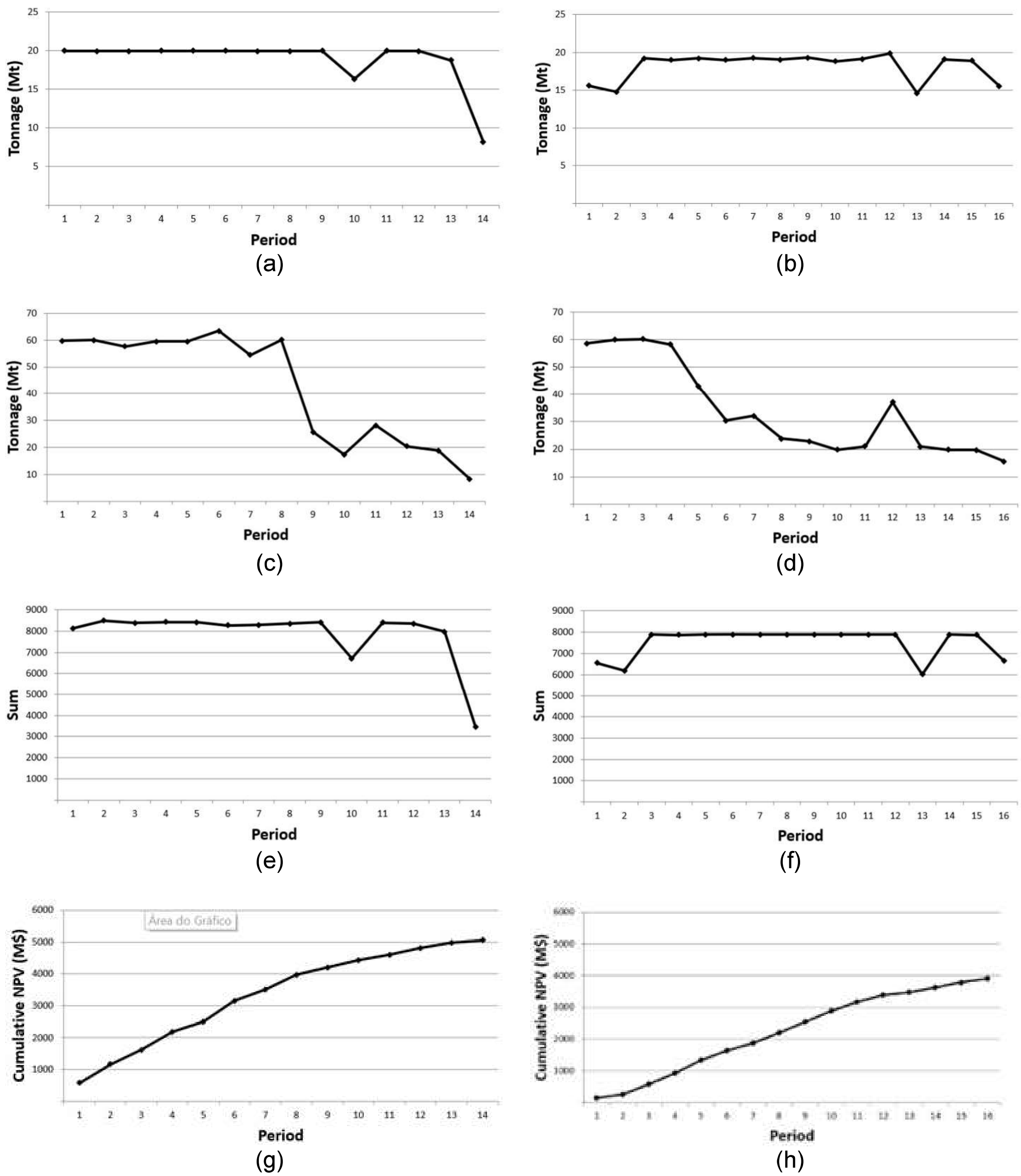


FIG 11 – (Left side) Marvin: (a) processing capacity; (c) mine capacity; (e) processing time; (g) net present value. (Right side) MarvinGeomet: (b) processing capacity; (d) mine capacity; (f) processing time; (h) net present value.

In the Marvin scenario, the processing capacity was respected and was kept at less than 20 Mt/annum. The mine capacity was almost constant until period eight, and then it started to decrease until the end of the mine. The processing time overtook the availability of the plant (7884 hrs/annum), but in this scenario, the processing time was not included as a constraint. This result means that the Marvin scenario will not process the 20 Mt/annum ore target because of a lack of plant time availability. This situation usually happens in mining projects when there is insufficient information about ore hardness variability. The net present value (NPV) for the Marvin scenario was 5055.4 MUS$ with a Life-of-mine (LOM) of 14 years. In the MarvinGeomet scenario, the processing capacity varied during the LOM because the processing time was considered a constraint. The mine capacity decreases during the LOM. The processing time was kept at less than 7884 hrs/annum, and the NPV obtained was 3894.6 MUS$ with an LOM of 16 years. Figure 12 shows periods 4, 8, and 12 for Marvin and MarvinGeomet scenarios.

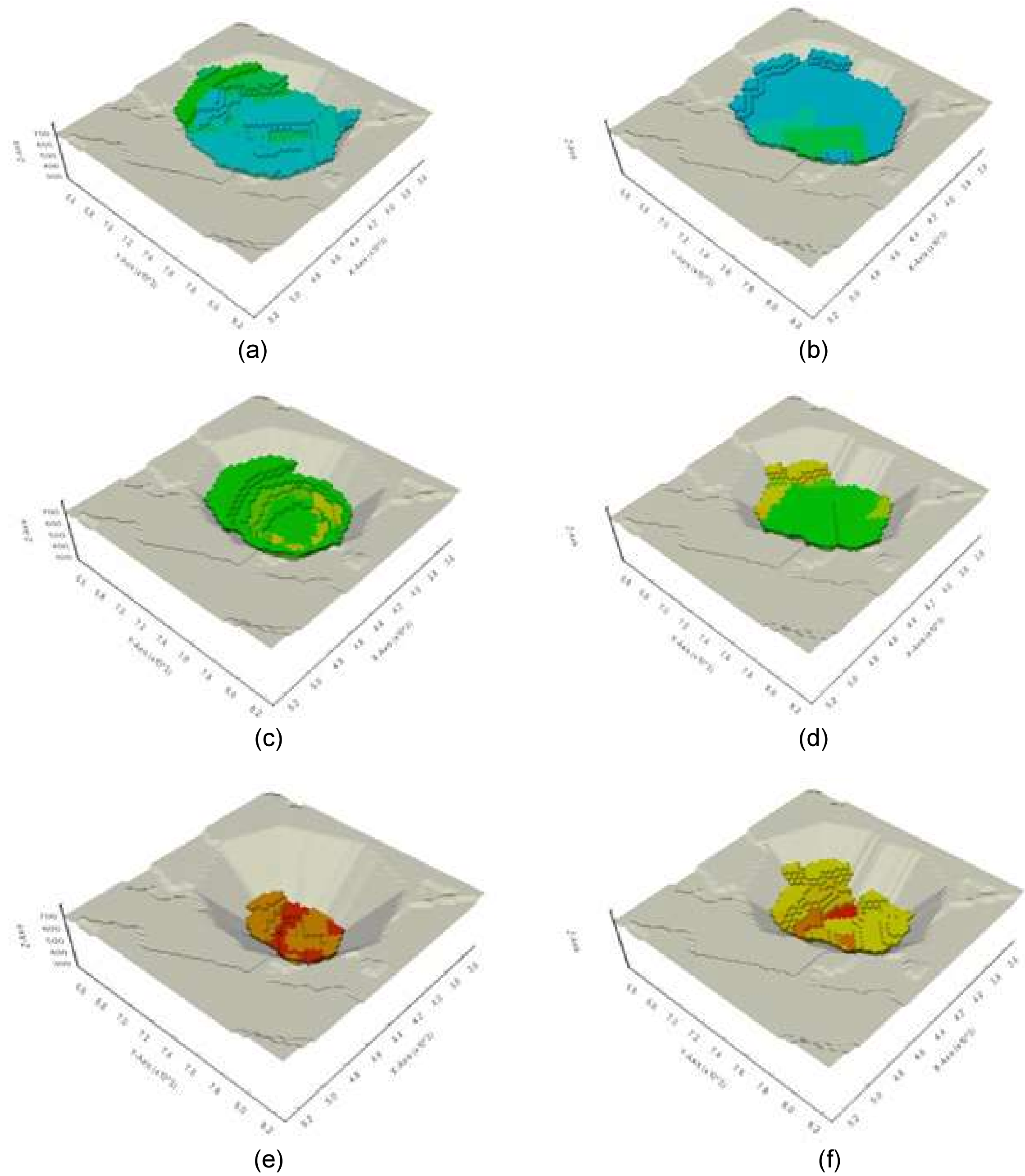


FIG 12 – (Left side) Marvin: (a) period 4; (c) period 8; (e) period 12.
(Right side) MarvinGeomet: (b) period 4; (d) period 8; (f) period 12.

The blocks selected for each period in each scenario were different once the processing cost was fixed in the Marvin scenario, and the processing cost varied due to the ore hardness of each block in the MarvinGeomet scenario. The mine scheduling algorithm must select blocks to maximise the value while respecting the processing time.

CONCLUSIONS

In this article, we showed how to estimate the processing plant capacity based on the ore hardness variability based on geometallurgy characterisation aiming to increase productivity and forecast possible bottlenecks in advance. The comminution indices can be transformed into specific energy and then, into processing time. Using this information, it is possible to have a constraint in the mine schedule optimisation model that considers the maximum operational hours of the processing plant. Then, the mine scheduling algorithm used, MiningMath in this case study, will select blocks to maximise the value while respecting the processing time.

Two scenarios were investigated, the first called Marvin and the second called MarvinGeomet. In the Marvin scenario, the processing capacity was respected (<20 Mt/annum), but the processing time surpassed the availability of the plant (<7884 hrs/annum). In this scenario, the processing time was not included as a constraint. This result means that the Marvin scenario will not produce 20 Mt/annum once there is no processing time available to achieve this production and the plant will be a bottleneck to this project. Without the ore hardness variability of the deposit, it is not possible to forecast the production correctly. The net present value (NPV) for the Marvin scenario was 5055.4 MUS$ with 14 years of Life-of-mine (LOM). In the MarvinGeomet scenario, the processing capacity varied during the LOM because the processing time was considered as a constraint. The time availability of the plant was respected (<7884 hrs/annum) and the NPV obtained was 3894.6 MUS$ with 16 years of LOM. In this scenario, we are close to reality since the mine scheduling optimisation looked for high-value blocks and respected their processing time to feed the plant.

The NPV of Marvin scenario is unrealistic once the processing cost was fixed for all blocks nor considering the ore hardness variability of the orebody. As a result, the NPV of this scenario is considerably higher when compared with the MarvinGeomet scenario. In the MarvinGeomet scenario the processing cost varied block-by-block due the time necessary to process it. This scenario is more realistic and can show future bottlenecks.

For future work, we suggest using this approach in a stochastic mine schedule model and also applying it to other commodities. The specific energy is a part of the milling costs and costs related to wear (balls and liners) should be considered in future studies.

ACKNOWLEDGEMENTS

The first and the last authors would like to thank CNPq (National Council for Scientific and Technological Development - grant 302629/2023) for partially funding the work.

REFERENCES

Bailey, C, Lane, G, Morrell, S and Staples, P, 2009. What Can Go Wrong in Comminution Circuit Design?, In Proceedings of the Tenth Mill Operators' Conference (The Australasian Institute of Mining and Metallurgy: Melbourne).

Bergeron, Y, Kojovic, T, Gagnon, M-d-N and Okono, P, 2017. Applicability of the HIT for Evaluating Comminution and Geomechanical Parameters from Drill Core Samples—The Odyssey Project Case Study, in Proceedings of the COM 2017, Vancouver, Canada.

Bienstock, D and Zuckerberg, M, 2009. A new LP algorithm for precedence constrained production scheduling, *Optimisation Online*, pp 1–33.

Bueno, M P, Almeida, T, Lara, L and Powell, M, 2024. The Geopyörä Index: A New Instrument for Assessing Comminution and Rock Strength Parameters, in Proceedings of the IMPC, Washington, USA.

Deutsch, M, Dağdelen, K and Johnson, T, 2022. An Open-Source Program for Efficiently Computing Ultimate Pit Limits: MineFlow, Natural Resources Research.

Doll, A, 2025. SMC Test parameters from A×b [online], Linkedin. Available from: <https://www.linkedin.com/in/alex-doll-66b57465/>

Espinoza, D, Goycoolea, M, Moreno, E and Newman, A, 2012. MineLib: A library of open pit mining problems, *Annals of Operations Research*, 206(1):91–114.

Global Mining Guidelines Group (GMG), 2021. The Morrell Method to determine the efficiency of industrial grinding circuits. Available from: <https://gmggroup.org/wp-content/uploads/2024/07/GUIDELINE_The-Morrell-Method-to-Determine-the-Efficiency-of-Industrial-Grinding-Circuits_2021-1.pdf>

Global Mining Guidelines Group (GMG), 2025. Introduction to Geometallurgy. Available from: <https://gmggroup.org/introduction-to-geometallurgy-white-paper/>

Hochbaum, D S, 2001. A new-Old algorithm for minimum-cut and maximum-flow in closure graphs, *Networks: An International Journal*, 37(4):171–193.

Johnson, T B, 1968. Optimum open pit mine production scheduling, PhD thesis, Operations Research Department, University of California, Berkeley.

Lerchs, H and Grossmann, I F, 1965. Optimum Design of Open Pit Mines, *CIM Bulletin*, 58:47–54.

Letelier, O R, Espinoza, D, Goycoolea, M, Moreno, E and Muñoz, G, 2020. Production Scheduling for Strategic Open Pit Mine Planning: A Mixed-Integer Programming Approach, *Operations Research*, 68(5):1425–1444.

Minelib, 2025. Datasets. Available from: <https://mansci-web.uai.cl/minelib/> [Accessed: 5 March 2025].

Minemax, 2025. A Simple Explanation of a Potentially Game-changing New Mine Planning Technology. Available from: <https://www.minemax.com/news/game-changing-new-mine-planning-technology/> [Accessed: 5 March 2025].

MiningMath, 2025. Knowledge Base. Available from: <https://miningmath.com/docs/knowledgebase/theory/algorithm/> [Accessed: 5 March 2025].

Varianemil, D, Kojovic, T, Hakim, D, Dilaga, R and Condori, P, 2023. Ore Hardness Mapping of Batu Hijau Ore Deposit Using the Hardness Index Tester, in Proceedings SAG2023, Vancouver, Canada.

APPENDIX

The pseudo-code of MiningMath optimisation algorithm.

```
INPUT: Block model,
      Mining parameters,
       Optional time limit T
OUTPUT: Excel report summarizing the main results of the optimization,
       Outputs of mining optimization, topography, and pit surfaces in
        .csv format that can also be imported into other mining packages.

EXECUTE initial assessment // Step 1
CREATE problem linearization P // Step 2
SET best_solution to empty
REPEAT // Step 3
    SOLVE P // Optimization engine + proprietary Branch & Cut algorithm
   SET LS to the integer, linear solution of P
   TRANSFORM LS to an integer, non-linear solution RS
    EVALUATE RS
        IF RS is better than best_solution THEN
            SET best_solution to RS
        ENDIF

       IF RS has violated constraints that were unviolated in LS OR
              has constraints that can be discarded/modified THEN
           CREATE new problem linearization P // Step 2
            SET R to TRUE
       ELSE
           SET R to FALSE
       ENDIF
UNTIL R = TRUE OR T has been reached
EXPORT reports and outputs from best_solution
```