

Inclusion of the geometallurgical variable specific energy in the mine planning using direct block scheduling

Jônatas Franco Campos da Mata ^{1*} 

Alizeibek Saleimen Nader ¹

Douglas Batista Mazzinghy ¹

Abstract

In mining projects, it is necessary to have a wide knowledge of the main variables of the mineral deposit before strategic mine planning takes effect. In the meantime, the application of geometallurgy has allowed the modeling of parameters related to the lithologies present in the deposit, such as the specific energy in comminution. This work intends to carry out a mine planning case study with the Direct Block Scheduling (DBS) methodology implemented in the MiningMath software and using the Marvin block model. The results indicate that the processing time of each block required more complex decision-making from the DBS algorithm to fulfill the objectives of mine planning. It is also noticed that the algorithms prioritize the extraction of blocks more released in the first years of the mine, anticipating profits and leaving, for the second half of the life of the project, the intensification of development, aiming to release more blocks for mining.

Keywords: Geometallurgical modeling; Specific energy; Strategic mine planning; Direct block scheduling.

Inclusão da variável geometalúrgica energia específica no planejamento de lavra utilizando sequenciamento direto de blocos

Resumo

Em projetos de mineração, faz-se necessário o amplo conhecimento das principais variáveis do depósito mineral antes da efetivação do planejamento estratégico de lavra. Neste interim, a aplicação da geometalurgia tem permitido o modelamento dos parâmetros relacionados às litologias presentes na jazida, como a energia específica de cominuição. Este trabalho pretende realizar um estudo de caso de planejamento de lavra com a metodologia de Sequenciamento Direto de Blocos (SDB) implementada no software MiningMath e utilizando o modelo de blocos Marvin. Os resultados indicam que o tempo de processamento de cada bloco exigiu do algoritmo de SDB tomadas de decisão mais complexas para cumprir os objetivos do planejamento de lavra. Percebe-se, também, que os algoritmos priorizam a extração de blocos mais liberados nos primeiros anos da mina, antecipando lucros e deixando, para a segunda metade da vida do projeto, a intensificação do desenvolvimento, visando liberar maior quantidade de blocos para a lavra.

Palavras-chave: Modelamento geometalúrgico; Energia específica; Planejamento estratégico de lavra; Sequenciamento direto de blocos.

1 Introduction

For Whittle et al. [1], mine planning is the methodology that defines the mining scheduling of blocks, ensuring the maximization of the Net Present Value (NPV) of the project and respecting certain operational and production constraints imposed on the project. According to Elkington and Durham [2], two important methodologies for determining the optimal pit can be highlighted. The conventional mine

planning methodology, widely used by mining companies, is known as the aggregation approach, and is based on the algorithms devised by Lerchs and Grossmann [3]. The other methodology, Direct Block Scheduling (DBS), in turn, is an innovative methodology and has been increasingly used in recent years. It was initially studied by Johnson [4], being classified as a block-level resolution approach.

¹Departamento de Engenharia de Minas, Universidade Federal de Minas Gerais, Belo Horizonte, MG, Brasil.

*Corresponding author: jonatas.mata@ufvjm.edu.br



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1.1 Lerchs-Grossman

Newman et al. [5] highlight three negative aspects of the approach based on Lerchs-Grossman: use of a fixed cut-off grade, which arbitrarily differentiates ore and waste rock blocks; use of a hypothetical preliminary price of the commodity, making gradual increments for the definition of nested pits; and fragmented optimization process, disregarding the influence of time on required resources. Such problems can lead to a reduction in the global NPV, as there is the possibility, for example, of discarding blocks of grade below the cut-off that can present potential positive financial results, due to the combined analysis of other specific variables.

1.2 Direct block scheduling

Johnson [4] devised the Direct Block Scheduling (DBS) methodology, a technique that only in recent years has been made viable for commercial applications. Some reasons for the late development of this methodology can be highlighted: significant increase in the processing capacity of computers from the first decade of the 21st century onwards; growing interest in probabilistic mine planning models; and improvement of program decision artifices [6]. In their studies, Miranda and Nader [7] highlighted important benefits of the DBS: availability of the optimal pit and mine sequencing in a single step, without the need to generate push-backs and nested pits, as is done by the traditional methodology; the existence of easy-to-operate tools to establish different scenarios; tools to work with intermediate stocks; and the possibility of including geometric restrictions, such as maximum vertical advance rate and minimum mining width, making the solution closer to operational reality.

1.3 Geometallurgy applied to mine planning

For Deutsch [8], the objective of Geometallurgy is the consistent addition of value to the business, in order to obtain economic gains in all the operations of the company. Morales et al. [9] carried out simulations of the strategic planning of an open-pit mine, incorporating geometallurgical parameters to the block model of the studied mineral deposit to analyze different scenarios. Expressive gains in the NPV of mining projects and reduction of overall costs were obtained, compared to the results obtained without the inclusion of geometallurgical parameters in the model. Traditionally, the main guiding parameter for mine planning is the content of the useful element.

Meanwhile, the mining engineer seeks to stabilize the grades for the processing plant, aiming at achieving the products within the specifications required by the market. However, there are other characteristics, intrinsic to each mineral type, that influence the performance of each mining block in the beneficiation plant. One can mention, for example, the specific energy used to break rocks fed into the plant. Due to the typological variability of the mineral deposit,

variations may occur in the competence of the rocks and, consequently, significant changes in the productivity and costs of crushing and grinding, depending on the mining fronts being extracted. Through geometallurgical studies, it becomes possible to model these performance variables and include them in the calculation of the block economic value [10].

1.4 Objectives and contributions of this research

The comminution represents the higher cost of the mineral processing plant and the variable specific energy is not currently been included in the block model by mining companies. This research is presenting a methodology to include the specific energy into the economic block value calculations allowing to obtain a more reliable mine planning in the future.

2 Materials and methods

2.1 Dataset

For the simulations in this study, the Marvin block model was used. This model is publicly available on the Minelib website [11], representing a copper and gold mine and having the following parameters per block: dimensions, location (coordinates X, Y and Z), economic parameters (USD), copper grades (%) and gold grades (ppm). The Marvin database consists of 53,271 blocks, with dimensions equivalent to 30 m x 30 m x 30 m. The block model considered the following variables: density (t/m^3), slope angle (degrees), processing time (h) and fixed process recoveries (88% for copper and 60% for gold). According to MiningMath [12], the economic values of each block are calculated by the user, being treated as software input data. The possible destinations are defined through the mathematical model of the software, depending on the economic values of each block, plant, stockpile or waste pile.

2.2 Scenario

In this study a scenario for mine planning was established considering the specific energy varying block by block and the material hardness increasing with depth. Some initial constraints were introduced into the MiningMath software. Intervals of copper and gold contents were also established for feeding the plant, in order to guarantee the stability of the processing plant. The range of copper grades was between 0.3% and 0.7%, while the grades fed from gold were restricted to the range between 0.3 ppm and 0.7 ppm. Another operational constraint considered was the maximum overall annual processing hours for the mining blocks. For this criterion, a horizon, per annual period, of 365 days, 24 hours a day of operation and operating yield of 90% was

adopted. Thus, the overall processing time (T_{PG}), in hours, is calculated as shown in Equation 1.

$$T_{PG} = 365 * 24 * 0,90 = 7,884 \quad (1)$$

It is known that the price of copper and gold metals, in the international market, has shown significant appreciation. Thus, the following updated prices were adopted for the simulation, coming from the LME website [13]: copper sales price = 7,034.00 USD/t; gold selling price = 59.70 USD/g. The other economic parameters, indicated on the Minelib website, were kept unchanged. Some geometric issues of the pit were also fixed, such as: slope angle; minimum mine width; minimum bottom width; and maximum vertical rate of advance. These variables are influenced by the size of the equipment and by the pit depth [12]. The discount rate to be applied was set at 10%. In addition, the maximum movement tonnages in the extraction (mine) and processing (plant) stages were fixed, considering quantities informed in Minelib [11]. Table 1 presents the values adopted for the operational constraints.

In order to make this simulation as feasible as possible, the Sossego Project, an important copper and gold mining located in Brazil, was taken as a base. According to Bergerman et al. [14], some characteristics of the milling plant in this project can be highlighted: SABC configuration (SAG mill with pebbles crusher followed by two ball mills closed with hydrocyclones), typical global specific energy values of the ore fed into the mill are between 17 to 20 kWh/t and nominal installed power of SAG and ball mills of 37,000 kW. For the modeling of the specific energy variable per block, the same installed power of the Sossego Project (37,000 kW) was adopted, but the range of specific energy values was different. To generate the values, the deposit was divided into 17 levels, considering an increasing correlation between the specific energy and the mine depth. It is known that deeper rocks remain fresher and unaltered, presenting greater hardness. For the most superficial level, specific energy of 10.0 kWh/t was assigned, with increments at each level until reaching 17.0 kWh/t at the deepest level. Equation 2 presents the calculation of global throughput for each block.

$$T = \frac{P}{E} \quad (2)$$

Table 1. Operational Constraints

Range of Cu grades on the process plant feed (%)	0.3	0.7
Range of Au grades on the process plant feed (ppm)	0.3	0.7
Slope Angle (°)	45	
Minimum mine width (m)	100	
Minimum bottom width (m)	100	
Maximum vertical rate of advance (m)	150	
Discount rate (%)	10	
Maximum moved tonnage of the mine (t)	60,000,000	
Maximum ore processing tonnages (t)	20,000,000	
Overall processing time (hours)	7,884	

Where: T = Throughput (t/h); P = Installed power (37,000 kW); E = specific energy (kWh/t).

For each block, the processing time in the plant will be calculated by Equation 3.

$$T_P = \frac{M}{T} \quad (3)$$

Where T_P = processing time (h); M = block mass (t).

The variation in processing time causes changes in the respective process cost, as a block with longer residence time in the plant will bring increased wear to crushers and mills, as well as lead to increased consumption of electricity and other inputs directly applied to mineral processing. Therefore, this study took into account the direct dependence of the process cost in relation to the T_P . For $T_P = 21.9$ h, which corresponds to the average value of the model, a process cost of 4.0 USD/t was assigned. For blocks with higher or lower T_P , the process cost was calculated proportionally. Table 2 presents the input parameters used.

2.3 Economic block value

In the simulated scenario, the mine planning was directed towards meeting the required levels of feeding the plant, in addition to incorporating the geometallurgical variable energy specific to each block. Equations 4 and 5 present the economic block value for ore blocks and waste rock, respectively.

$$\text{Process} = (VB \cdot d) \cdot \left[\frac{(t_{Cu} \cdot R_{Cu}) \cdot (SP_{Cu} - SC_{Cu}) + (t_{Au} \cdot R_{Au}) \cdot (SP_{Au} - SC_{Au})}{(t_{Au} \cdot R_{Au}) \cdot (SP_{Au} - SC_{Au})} \right] - [(VB \cdot d) \cdot (CP + CM)] \quad (4)$$

where Process = economic value of ore blocks (USD); V_B = block volume (m^3); d = density of block (t/m^3); t_{Cu} = Cu grade (%); R_{Cu} = Cu process recovery; SP_{Cu} = selling price of Cu (USD/t); SC_{Cu} = selling cost of Cu (USD/t); t_{Au} = Au grade (ppm); R_{Au} = Au process recovery; SP_{Au} = selling price of Au (USD/g); SC_{Au} = selling cost of Au (USD/g); C_P = Process cost (USD/t); C_M = Mine cost (USD/t).

$$\text{Waste} = -(VB \cdot d) \cdot (CM) \quad (5)$$

Where Waste = economic value of waste blocks (USD).

Table 2. Input parameters

Input parameters	Cu	Au
Recovery	88%	60%
Specific Energy (kWh/t)		Variable
Processing Time (hours)		Variable
Process Cost (USD/t)		Variable
Mine Cost (USD/t)		0.9
Selling Price (USD)	7,034.00	59.70
Selling Cost (USD)	720	0.20

3 Results and discussion

Table 3 presents a summary of the overall simulation results.

Figure 1 expresses the evolution of the NPV over the life of the project.

There is a significant growth in NPV until year 9, with a gradual reduction in the annual increments of this parameter from that year onwards. This behavior can be related to the increase in processing times in each block as the open pit is deepened, causing an increase in processing costs in the plant. Figure 2 presents a comparison of the ore production and Stripping Ratio (SR) during all project periods.

In the first phase, the SR starts at 0.24, gradually increasing until it reaches 3.78 in year 10. That is, in the first years there is a greater number of ore blocks released, requiring less mine development. As the life of the project progresses, additional efforts are required to release ore to meet the production plan, until it peaks in the tenth year. From then on, the SR was reduced to levels between 0.19 and 1.38, demonstrating that the extraction of waste blocks only for the continuity of mining. Regarding ore production, the target defined in Table 1 was reached during the life of mine (LOM). Exceptions occurred in

year 10 (12.5 Mt), which coincides with the maximum waste extraction, and in year 20 (1.29 Mt), due to open pit exhaustion. Figure 3 displays the global mass movement along the LOM.

The mass movement increases from year 1, with a peak of 59.56 Mt in year 10. Then, it continuously reduces until reaching 3.07 Mt in year 20. This parameter was predominantly influenced by the extraction of waste, since the ore production presented values around 20 Mt. Ore production was low only in years 10 and 20, as shown in Figure 2. Figure 4 shows the open pits for years 4, 8, 12 and 16.

Figure 4 shows that the development and mining of the deposit took place in two distinct phases, seeking to balance the costs involved in extraction and processing. The pits of years 4 and 8 are part of the first half of the LOM, in which the stripping ratio gradually increased and mining was directed to richer and more profitable blocks. In this context, the aim was to maximize the horizontal extension in the mine development, as the deeper blocks had lower process times and processing costs. During the 12th and 16th years, in turn, the stripping ratio was constantly reduced and deeper blocks were extracted, therefore more expensive in terms of processing.

Table 3. Simulation results

Periods (years)	20
NPV (MUSD)	6,443.4
Plant Feed (Mt)	369.40
Waste (Mt)	400.77
Stripping Ratio (SR)	1.08
Metal Production – Cu (kt)	1,644
Metal Production – Au (kg)	152,230.6
Average Processing Time (h)	6,738.9
Average Cu grade - Ore (%)	0.50
Average Au grade - Ore (ppm)	0.46
Average Cu grade - Waste (%)	0.04
Average Au grade - Waste (ppm)	0.04

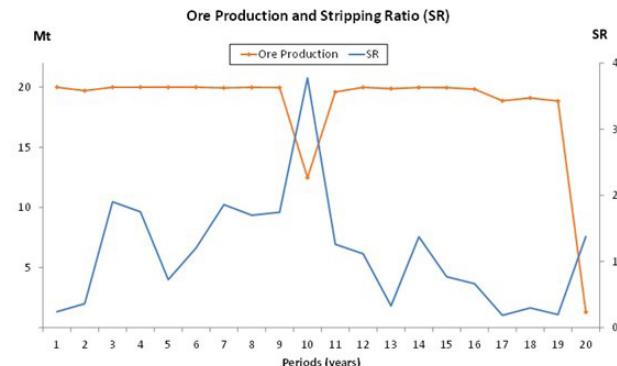


Figure 2. Ore and waste extracted year after year.

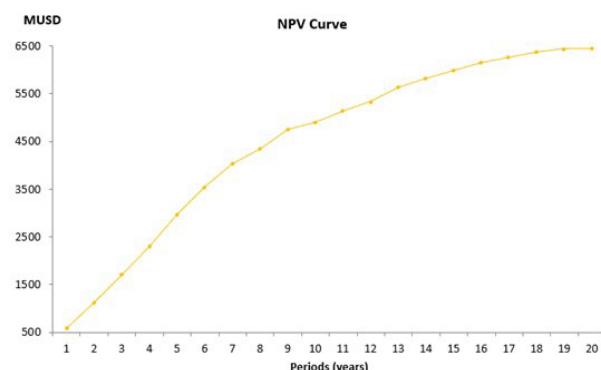


Figure 1. Evolution of the NPV during the LOM.

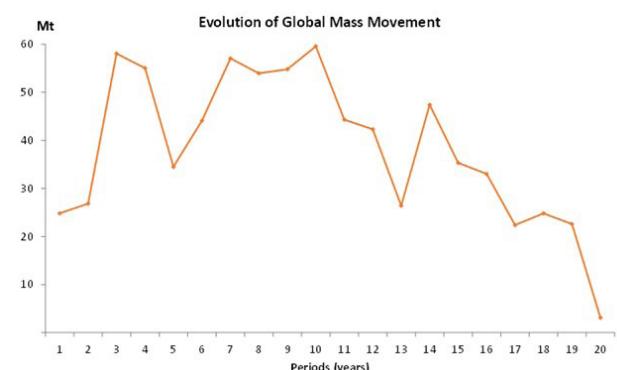


Figure 3. Evolution of global mass movement.

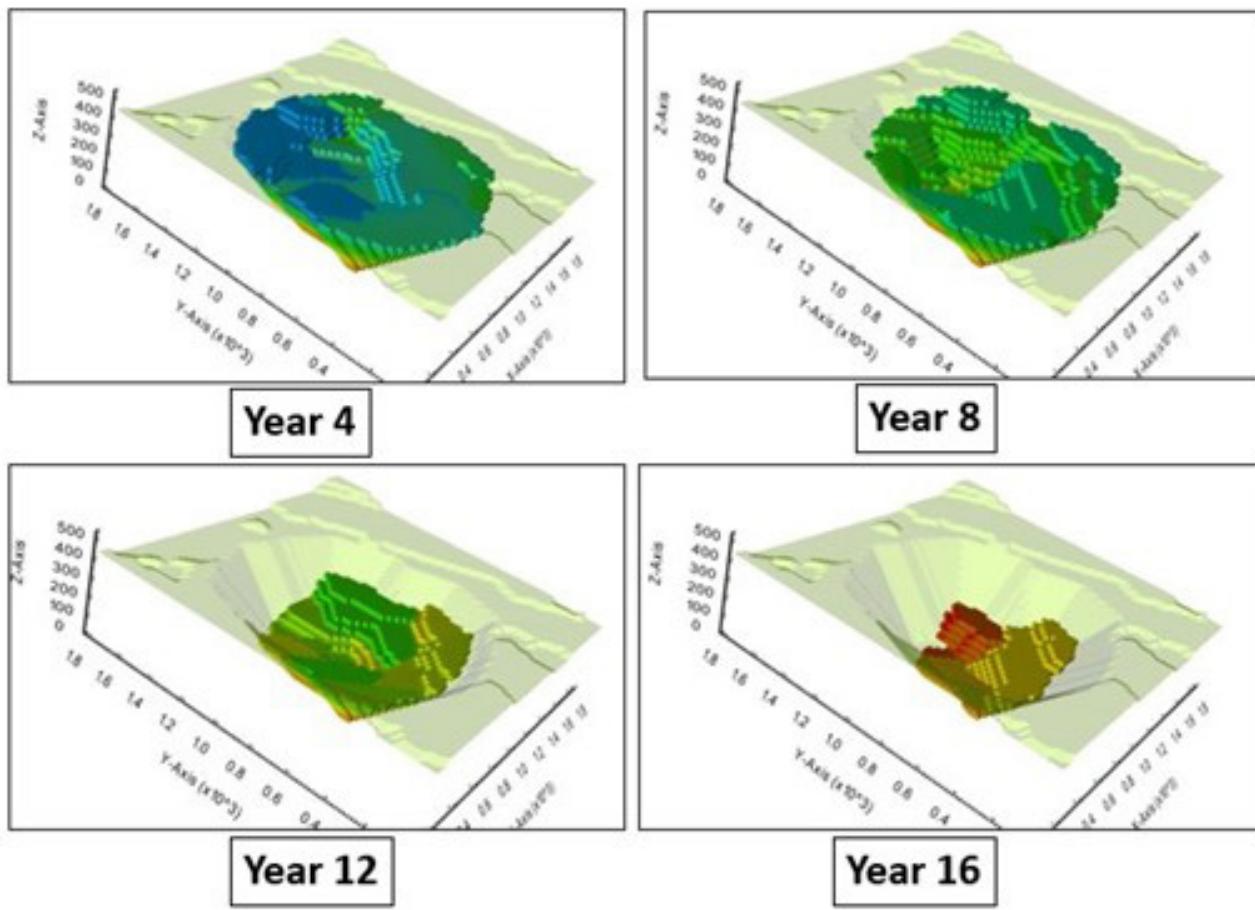


Figure 4. Open pits in the years 4, 8, 12 and 16.

4 Conclusions

Overall, the simulation demonstrated the importance of integrating geometallurgical modeling of mineral deposit variables with innovative mine planning methodologies such as DBS. The geological and process knowledge, when done in detail and applied to the block model, can provide the planner with decision tools for a better understanding of the LOM. The scenario considered several operational restrictions, in addition to incorporating specific energy as a geometallurgical variable. The gradual elevation of this parameter from the surface to the deepest level was taken into account, considering the premise that lithologies not subject to weathering tend to have greater hardness. When running this simulation, it was possible to notice that there is a continuous increase in the Stripping Ratio (SR) from year 1 to year 10, due to the need to develop the mine to comply with the production. From year 11 onwards, the SR is reduced, extracting only enough amounts of waste to release the expected ore. Ore production is at an adequate level throughout the LOM. The exceptions are the tenth and twentieth years, due respectively to the SR peak and open-pit exhaustion.

The NPV rises more aggressively until year 9, and then shows smaller increases until the end of the LOM. This behavior is related to the continued increase in block processing times at higher depths, increasing process costs and reducing financial gains. The implementation of geometallurgy helps considerably in the precision of mine planning, as it allows a more detailed understanding of the variability of the parameters that influence the operational performance of the mine and the plant. The authors are suggesting future studies considering scenarios with a production ramp-up in the first years of the LOM, the constraint of mass movement range for different periods and the use of ore stockpiles.

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