Short-term mine scheduling targeting stationary grades

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Abstract

In short-term mine planning, mining scheduling is generally defined by designing dig-lines, allocated on benches. The mined ore will be sent to stockpiles, homogenization piles, or a concentration plant. The process to design dig-lines is usually done manually, whereby multiple simultaneous mining fronts are time-consuming and labour-intensive. The manual design of dig-lines tends to produce high variability of the grades throughout certain periods. Due to the limited time to manually multiple test dig-line design alternatives in short term planning, it is impossible to ensure production under stationary mean grades and variance. This article proposes an alternative to design short-term dig-lines, through an optimization process that joins and sequences the blocks in the block model over weeks or months, ensuring low variability of grades among periods. The methodology proposed generates multiple random paths starting at seed-points representing the locations and numbers of shovels previously selected by the mine planner. It tests multiple polygons representing a set of first dig-lines, comparing them with others, and keeping the dig-lines of low variability closer to a specific ore grade probability distribution, discarding the rest of the iterations. The process is repeated for the next dig-line. The block grades' probability distribution of all iterations is compared to a reference-grade histogram, and the iterations with the grade histogram more adherent are selected. Union-find and genetic algorithms were used to optimize the dig-lines aiming at the possible stationary grade distribution. The mean and variance of the reference model are 2.13% and 0.64%^{2}, respectively. The mean for the automated draw dig-lines is closer to these values than the ones manually drawn. The method ensures more constant quality and quantity of ore production along a period planned, matching a target grade probability distribution. The methodology is illustrated using SiO_2 values at a major iron ore mine.

Keywords: short-term planning, block sequencing, stochastic planning, genetic algorithm.

1. Introduction

Short-term mine planning aims to ensure the quality and quantity of ore according to the production scheduled by long-term planning (Hustrulid *et al.*, 1995). In long-term mine planning, models are based on widely spaced drilling, which is gradually filled in as the project advances. Models are usually updated on a yearly basis with information acquired from new drill holes (Rossi and Deutsch, 2013). With high accuracy, precision and high cost, these data lead to the estimation of blocks with increasingly smaller dimensions. Therefore, short-term planning provides detailed procedures for executing the mine planning at the operational level and involves intensive planning, including shift-by-shift schedules. Based on drill holes, the high-precision estimation may be insufficient for the resolution at small time scales (1 month for example), so the incorporation of short-term data is necessary. One of the most challenging aspects of updating short-term models is updating the geological model and estimation domains using production data (Rossi and Deutsch, 2013) generating uncertainty on domains limits.

Many developments have been presented in updating the block model for short-term planning using geostatistical methods in the last decades. Ore production costs have increased (Dimitrakopoulos, 2011) due to the declining quality and increased complexity of the mineral resource. Thus, it is necessary to improve the accuracy of block models. Also, the re-estimation of models is usually performed using geostatistical methods based on data provided by densified meshes, using samples obtained from channels and drilling dust (Araújo *et al.*, 2018; Nelis and Morales, 2021). Consequently, a more agile and adaptive planning process is needed. These new data allow a local evaluation at a small block support, helping to select ore and waste (Santibanez *et al*., 2020).

Short-term planning, in most cases, is carried out manually to generate "to be mined" ore polygons in volumes that satisfy the needs of the processing plant. In addition, the restrictive factors associated with the mining phase, such as operational, technological, and environmental factors, are considered. The decision about which blocks should be sent to the concentration plant or the blending/homogenization piles is made based on polygons known as dig-lines, obtained by manual design, largely dependent on the ability of the mine planning engineer. The manual design of each dig-line is limited and does not allow the exploration of different possibilities (Toledo *et al*., 2017). Also, the manual definition of the dig-lines has the limitation of considering only one variable at a time (usually). This limitation cannot achieve the technological characteristics demanded by the processing plant, if multiple variables must be considered simultaneously. Another aspect being observed is that even if the mean grade in the dig-lines matches the short-term mining planning target, the grades can fluctuate within the dig-lines, causing a reduction in the performance of the processing plant (Toledo *et al*., 2017). There are some solutions in this area based on modern mixed integer programming (MIP). Smith (1998) studied the goal-programming MIP model to solve the short-term scheduling problem, aiming to maximize the ore production while taking into account blending constraints. L'Heurex *et al.* (2013) used MIP to determine which blocks would be extracted and the order, and found that the movement of shovels could allow the production capacity of equipment to be met in the short-term.

The proposed solution based on union-find and genetic algorithms allows blocks from initial excavation points located on exposed ore in benches, called production polygons. These blocks that together form dig-lines can be destined to piles or the beneficiation plant. The objective is for the dig-line to imitate the grades of a reference distribution. The idea is to provide a sequence of blocks grade with maximum similarity among each dig-line for a production period.

Therefore, this article proposes a fast and straightforward solution to managing grade fluctuations during short-term mine planning using algorithms to analyze the variability and sequence the blocks for multiple possible mineable polygons. The algorithm uses as a reference the global or local grade probability distribution function for the ore (Ribeiro *et al*., 2007; Toledo *et al*., 2017). Thus, the distribution of block grades of each possible dig-line keeps the one most similar to the target histogram. Note that dig-line grades come from subsets of blocks extracted from the ore reference-grade block model histogram. The proposal can be used on either estimated or simulated block models for short-term mining planning.

2. Materials and methods

The union-find algorithm operates data structure of disjoint sets to maintain a collection of non-overlapping elements of a finite universe (Patwary *et al*., 2010). The algorithm is used to prevent elements of a 3D array from being selected by two or more subsets and ensures the adherence of the elements representing ore blocks.

The first applications of genetic algorithms were in the field of biology. In the 1950s and 1960s, several computer scientists independently studied evolutionary systems and proposed that the theory of biological evolution could be used as an optimization tool for engineering problems (Mitchell, 1998). John Holland introduced genetic algorithm in the 1960s, and Holland (1992) presented genetic algorithms as an abstraction of biological evolution. Even though most of these algorithms were created in the 1970s, it was only 30 years later, that they were popularized and began to be considered a practical tool for everyone using a standard personal computer. When solving a problem with a genetic algorithm, instead of asking for a specific solution, the planner provides characteristics that the solution must have or rules that its solution must comply with to be accepted (Sheppard, 2017). Genetic algorithms are often considered to function optimizers, and there is a wide range of problems to which they can be applied (Whitey, 1994). Dendy and Schofield (1994), Alipour *et al*., (2020) used a genetic algorithm for scheduling open pit design.

In the short-term planning, the grades of exposed mineable blocks along benches are used. This short-term grade model is estimated using data from drill holes, trenches, channels, or blast hole dust. The selection of a block within a dig-line depends on operational issues (such as availability of the block – exposed or not), equipment availability, and its geographical position.

With the estimated short-term model, the process of generation of the optimal dig-lines starts by defining a certain period usually a month. A target parameter which must be controlled in feeding the processing plant or in the final product is selected. This study aim is to keep the distribution of block grades in every mining advance as close as possible to the target grade distribution.

The mine planner must define the starting point or multiple starting points from where the mining will start in the proposed optimization analysis. From there, the algorithm starts a random path that respects the operational mining constraints as bench limits, selects adjacent blocks of ore, number and locates the starting point, production, and period. The first possible dig-line will be generated. A set of scenarios with the same starting point and the same number of blocks is generated, following different random paths, generating multiple possible dig-lines.

Among the generated scenarios, the one with a set of block grades closest to the reference distribution is selected. The remaining scenarios are discarded. The best scenario is obtained using a quantile-quantile comparison between the distribution of the grades in the blocks (global model) and the distribution of the grades that have been generated in each scenario (iteration) using a least squares technique. Thus, a set of blocks in the first dig-line is obtained. The population of ore blocks is updated by removing the blocks included in this first dig-line. Next, a new set of dig-line alternatives is generated for the second advance. The dig-line grade distribution closest to the reference distribution is kept from this new set of alternatives. Figure 1 presents the proposed workflow to select each dig-line for short-term planning. An illustration case from an iron ore mine illustrates the workflow proposed considering two geological domains and two chemical species.

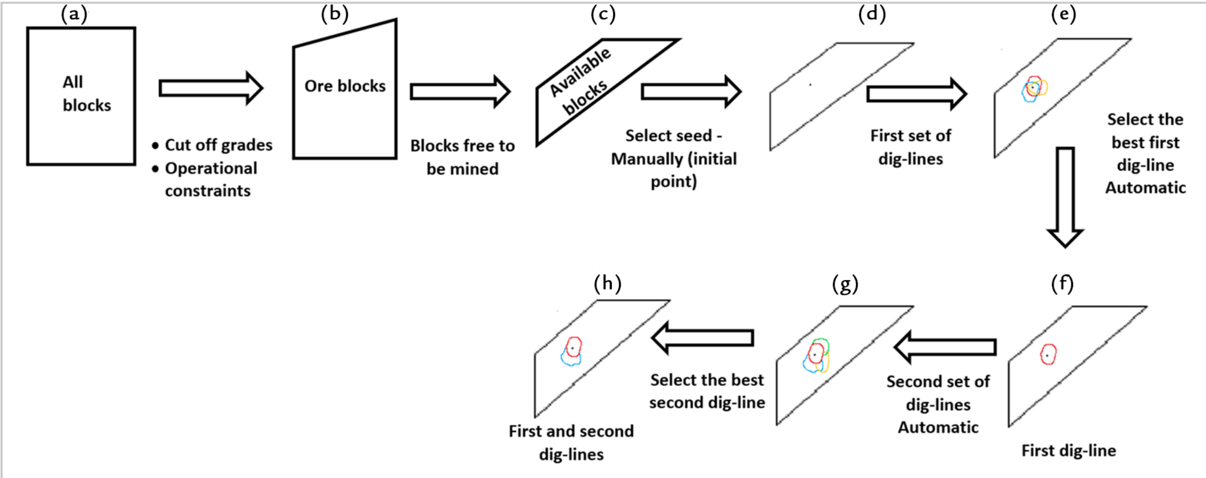

Figure 1 - Workflow adopted: a) short-term model one month, b) mining constraints (cut-off grades, contaminant limits.), c) available ore blocks – reference histogram grade model, d) definition of the starting point for mining – a seed for the random path, e) iteration of N possible first dig-lines around the seed, f) the best dig-line is the one that has a histogram of grades that matches the reference-grade model histogram, g) iteration of N possible second dig-lines, h) the second dig-line is the one that best matches the reference-grade model histogram.

2.1 Computational optimization

The optimization algorithm was implemented in Python 3 code, based on genetic algorithms, and tested on a block model estimated using ordinary kriging and a single variable to illustrate this case study. The algorithm can be expanded to work with geostatistical simulations with multiple variables. The algorithm is based on the following steps:

(i) An exposed portion is selected from the block model, corresponding to the upper two vertical benches. Mining constraints in the form of cut-off grades for the variables are applied in this example, SiO_2 should be less than or equal to 5%, while Fe should be greater than or equal to 56%, and the topographic limit of the bench.

(ii) Let Z_c be a set of T distinct elements, and $P1$ denote a subset of Z_c. Two sets $P1$ and $P2$ are disjoint if $P1 \cap P2 = \emptyset$. A disjoint-set data structure maintains a dynamic collection $\{P1, P2, \ldots, PT\}$ of disjoint sets that together cover the universe Z_c (Patwary *et al*., 2010). Taking Z_c as the reference ore block model forming the exposed outer shell, it is necessary to select the seed points where the optimization process starts using the Union-find algorithm (Tarjan, 1975). The algorithm selects blocks sequentially while respecting mining restrictions. Multiple mining alternatives are created, starting by mining from seed points. Figure 2 presents a selection scheme of blocks mimicking what happens for a sequence staring at two seed points. This sequence increases in complexity depending on the number of seeds and the number of elements.

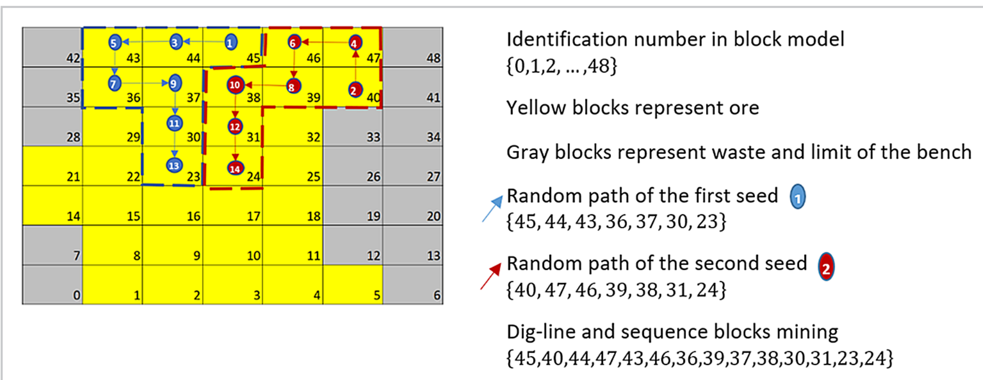

Figure 2 - Selection scheme of blocks for two shovels and seven blocks per each shovel.

(iii) Each mining alternative created in (ii) generated a subset of the ore block model that represents dig-lines. Compared to the others, the best match with the targeted histogram of the reference ore block model is selected. The algorithm works according to the following objective function or fitness equation:

$$Objective\ function = Min\left(\sum_{1}^{n}\sum_{0}^{k}\frac{(i_k - j_k^n)^2}{(i_k + j_k^n)}\right) \quad (1)$$

where: n: number of iterations
k: number of classes
i: reference histogram grade ore block model (target)
j: dig-line histogram grade subset ore block model.

Finally, the iteration chosen will be the one which is more similar to the reference histogram grade model. Thus, the process continues until the number of required blocks is selected.

(iv) Figure 3 illustrates the process of selecting each dig-line of Z_c, where q starting points represented number of seeds, dig-lines are represented by $\{P1, P2, \ldots, PT\}$ and the generated random iterations of subset model block (selected blocks) are represented by $\{S_1, S_2, \ldots, S_n\}$. From dig-line $P1$, the best fitness (iii) selected S_3 as the optimal by tournament selection compared the histogram of Z_c with the histograms of $\{S_1, S_2, \ldots, S_n\}$, and then, from the random iterations along dig-line $P2$, selected S_2 as the best fitness, and so on, following the orange arrows.

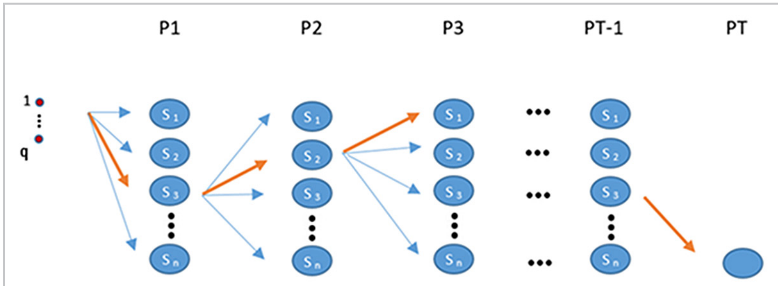

Figure 3 - Sequence adopted to select the mining advance within each dig-line.

As a result, a selection of blocks within each dig-line that approaches the characteristics of the ore feeding of the processing plant or for the final product quality planned by the long-term scheduling process. The entire process is repeated until all adjacent ore blocks are selected, obtaining successive mining advances with grades that are the closest possible match to the reference histogram grade read at the ore block model.

3. Results

The proposed methodology was tested on two benches of an iron ore mine with block dimensions of 10 × 10 × 10 meters. The monthly production considered is 842,400 t. The constraints are that Fe should exceed 56% and SiO_2 should be lower than 5%. Note that the sequencing algorithm considers only the SiO_2 variable due to its higher variance compared to the

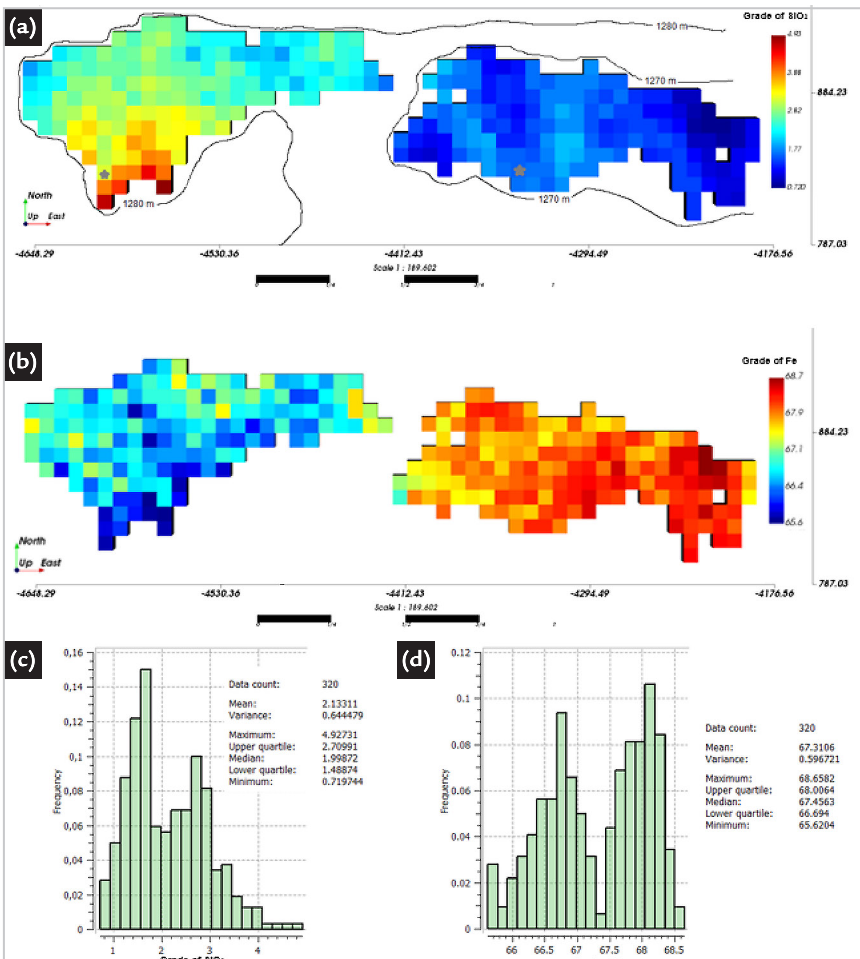

Figure 4 - a) Maps of reference grade model for for SiO_2,
b) maps of reference grade model for Fe, c) histogram and statistic for SiO_2, d) histogram and statistic for Fe.

variable Fe. Finally, the mean and variance of the resulting dig-lines are compared, using the proposed algorithm against the ones obtained by manually design.

Figure 4a presents the block model of SiO_2 with two benches at level 1280 and 1270 m. Only blocks less than 5% are shown at the two benches; the black dots represent the seeds or starting points where the shovels are placed. The histogram and statistics for these blocks are shown below. These are the target histograms formed by the grade blocks of two benches, which are pursued by each dig-line. Figure 4b presents the blocks in the model with their representative Fe grades. The parameters used in the algorithm are listed in Table 1. Figures 4c and 4d present the histograms and statistics for the SiO_2 and Fe models, respectively.

The parameters used to run the algorithm are presented in Table 1.

Table 1 - Input parameters.

Input data	Values
Cut-off <= SiO_2	5%
Cut-off >= Fe	56%
Number of blocks and tonnes per week	80 blocks and 210600 t
Number of iterations	20
Number of dig-line	4
Number of seeds	2
Coordinates for the starting points (x, y, z) (seeds)	(–4615, 823, 1280), (–4337, 834, 1270)

Figure 5 presents the cumulative histograms for multiple iterations (red), reference histogram the model grades (black), and the best cumulative histogram. The value of each iteration for the dig-line 1 obtained using Equation 1 is also shown. The lowest value refers to the most similar iteration to the reference histogram from model grades. Figure 5a shows the formation process of the first dig-line, showing less adherence due to the influence of the restricted area on the selected blocks, positions, and values of the seed points. The second and third dig-lines show better adherence because the search area is larger and the fourth dig-line is restricted to the rest of the area.

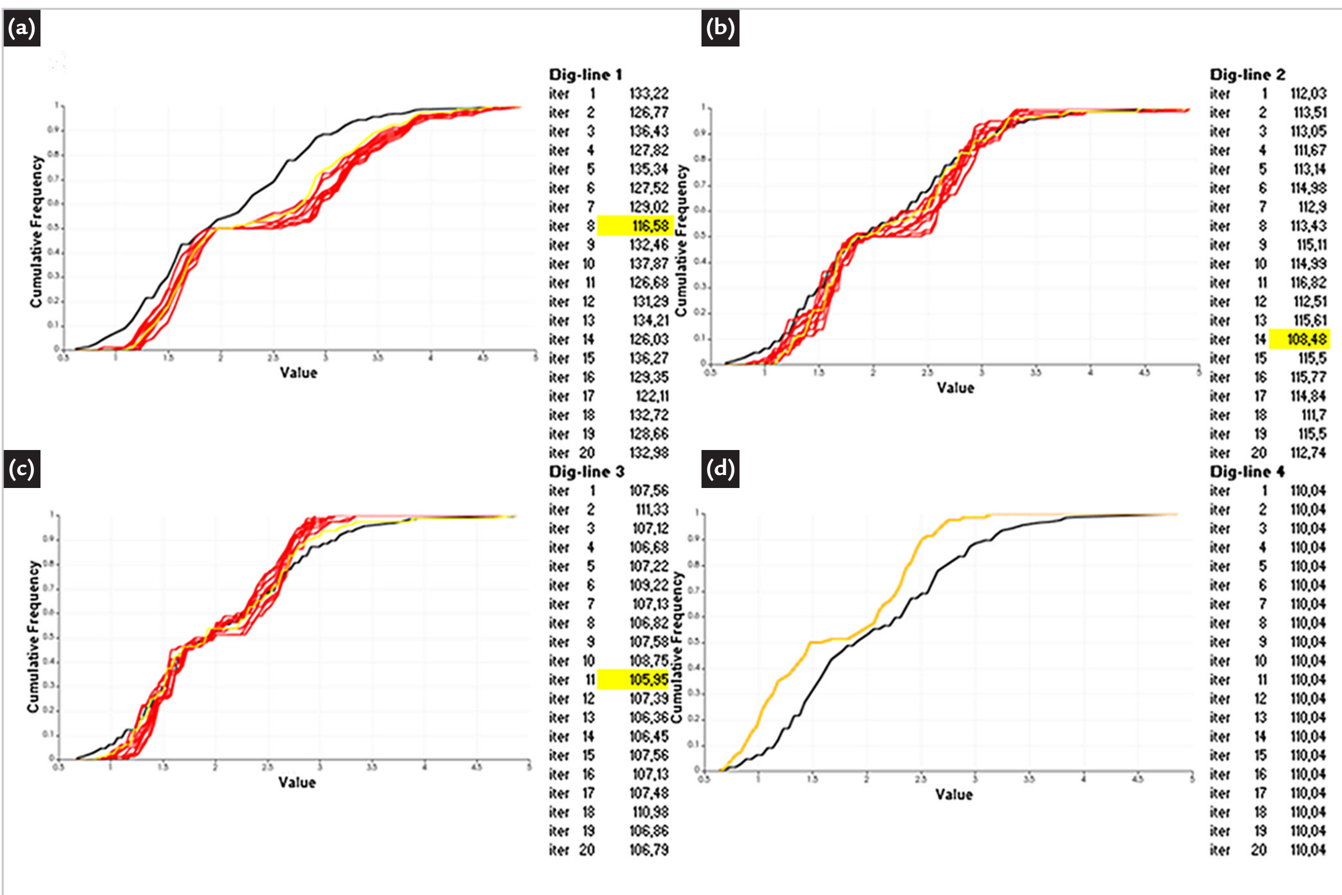

Figure 5 - Process of iterations and selection of the best dig-line:
a) dig-line 1 with 20 iterations, b) dig-line 2 with 20 iterations, c) dig-line 3 with 20 iterations, d) dig-line 4 with 20 iterations.

Figure 6 shows the cumulative histograms for the four selected dig-lines and the reference histogram grade model. Each curve depicts the grades from the blocks associated with each week. Below are the mining sequences adopted.

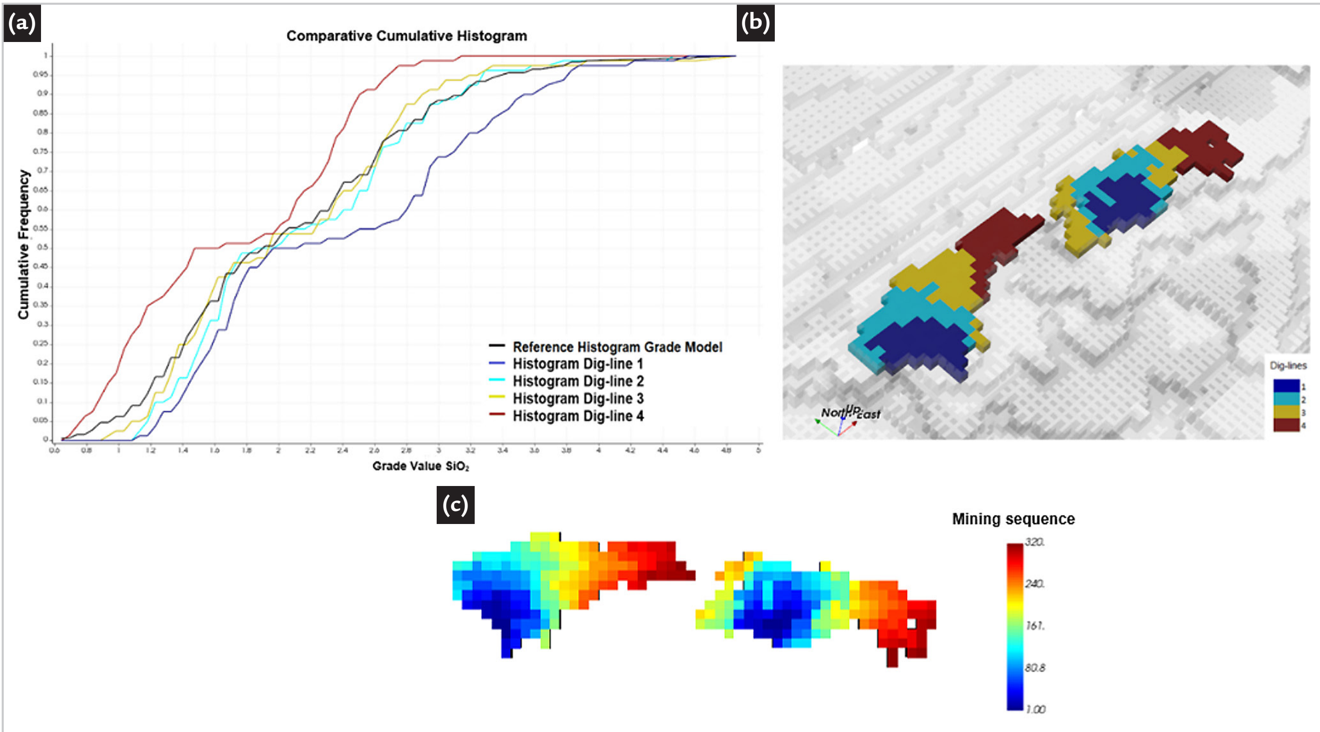

Figure 6 - a) Comparative cumulative histograms, b) map of dig-lines, c) mining sequence.

Table 2 presents the global statistics for the results, which are similar for the dig-lines corresponding to weeks 2 and 3 and less similar for weeks 1 and 4. The algorithm looks for the possible best combination considering the available blocks. If the available blocks do not provide grades close to the target model, the solution will not be a perfect match but will be the best possible one. Table 3 presents statistics for the same models for Fe values.

Table 2 - Statistics summary for reference model and each dig-line generated (SiO_2%).

	Mean	Mean dig-line/ Mean global	Variance	Standard deviation	Standard deviation relative	Max. value	Min. value	Number of blocks
Global	2.13	1.00	0.64	0.802	1.00	4.93	0.72	320
Week 1	2.44	1.14	0.79	0.886	1.10	4.67	1.23	80
Week 2	2.20	1.03	0.54	0.735	0.92	4.50	1.14	80
Week 3	2.13	1.00	0.56	0.750	0.94	4.92	0.99	80
Week 4	1.74	0.82	0.46	0.677	0.84	3.17	0.72	80

Table 3 - Statistics summary for the reference model and each dig-line (Fe%).

	Mean	Mean dig-line/ Mean global	Variance	Standard deviation	Standard deviation relative	Max. value	Min. value	Number of blocks
Global	67.31	1.00	0.60	0.775	1.00	68.66	65.62	320
Week 1	67.24	0.99	0.58	0.762	0.98	68.21	65.63	80
Week 2	67.28	1.00	0.62	0.787	1.02	68.46	65.68	80
Week 3	67.27	1.00	0.50	0.707	0.91	68.38	65.62	80
Week 4	67.44	1.00	0.69	0.830	1.07	68.66	65.84	80

Figure 7 represent the histograms for the grades of each dig-line selection were plotted against the target grade histogram previously stipulated. QQ-plots were generated between them and the reference month for SiO_2 values.

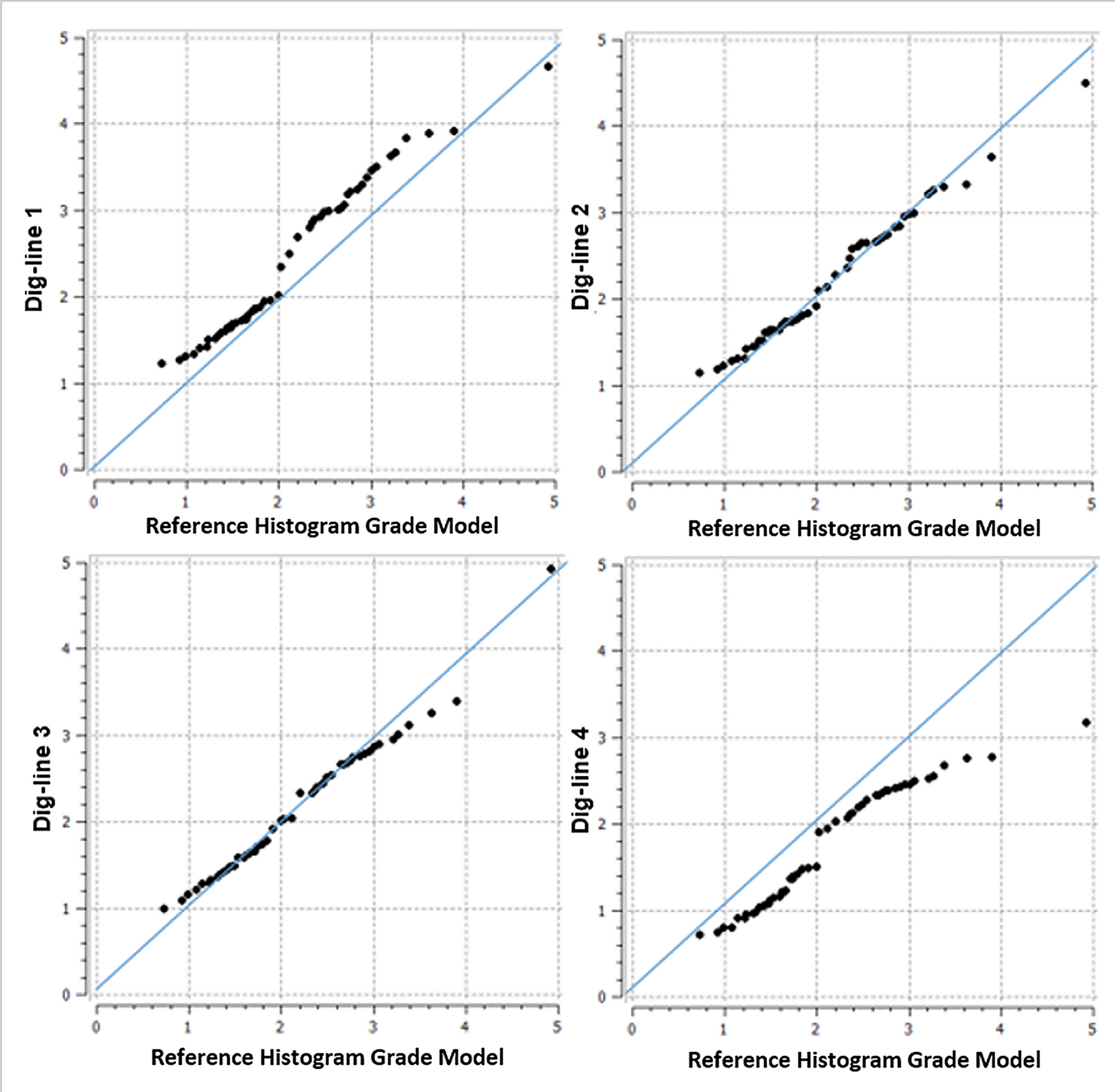

Figure 7 - QQ-plots of dig-lines, where the reference histogram grade model is on the X-axis and the histograms for dig-lines 1, 2, 3, and 4 are on the Y-axis.

3.1 Comparing the dig-lines generate by the algorithm versus manually drawn

Figure 8 presents the block model for SiO_2 overlayed by the manually designed dig-lines.

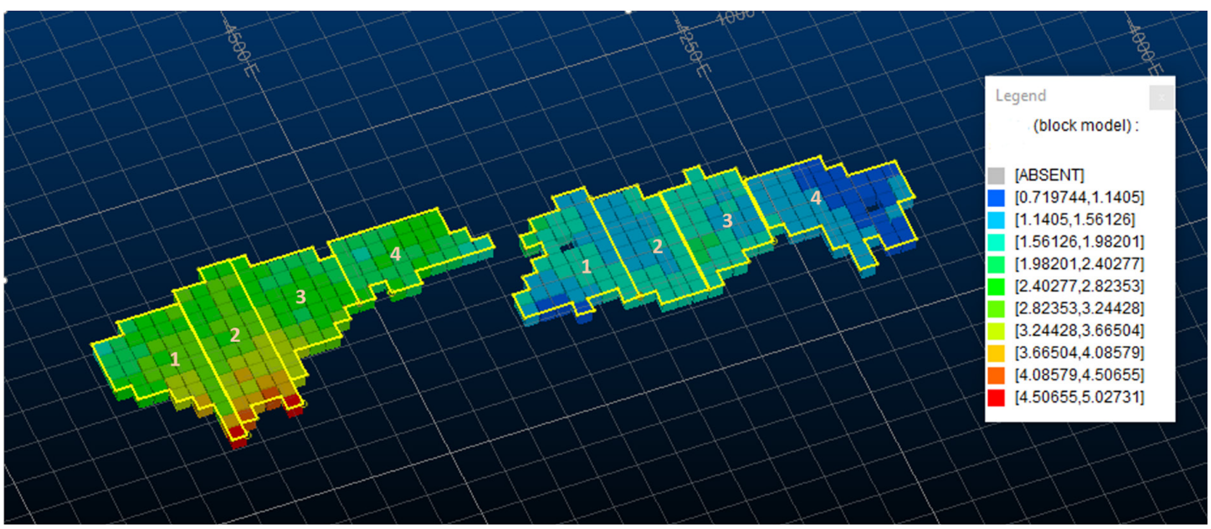

Figure 8 - Dig-lines 1, 2,3 and 4 manually drawn on the SiO_2 block model.

Table 4 presents the global statistics for dig-lines corresponding to weeks 1, 2, 3 and 4.

Table 4 - Statistics summary for the reference model and for each dig-line done manually (SiO_2%).

	Mean	Mean dig-line/ Mean global	Variance	Standard deviation	Standard deviation relative	Max. value	Min. value	Number of blocks
Global	2.13	1.00	0.64	0.802	1.00	4.93	0.72	320
Week 1	2.19	1.02	0.60	0.800	0.99	4.67	0.99	82
Week 2	2.48	1.16	0.91	0.954	1.14	4.93	1.14	78
Week 3	2.23	1.04	0.33	0.574	0.72	3.39	1.37	76
Week 4	1.65	0.77	0.38	0.616	0.77	2.94	0.72	84

Figure 9 compares the mean of the dig-lines designed by the algorithm, the mean of the dig-lines manually drawn, and the global average. Greater adherence to the global mean is observed in the dig-lines designed by the algorithm.

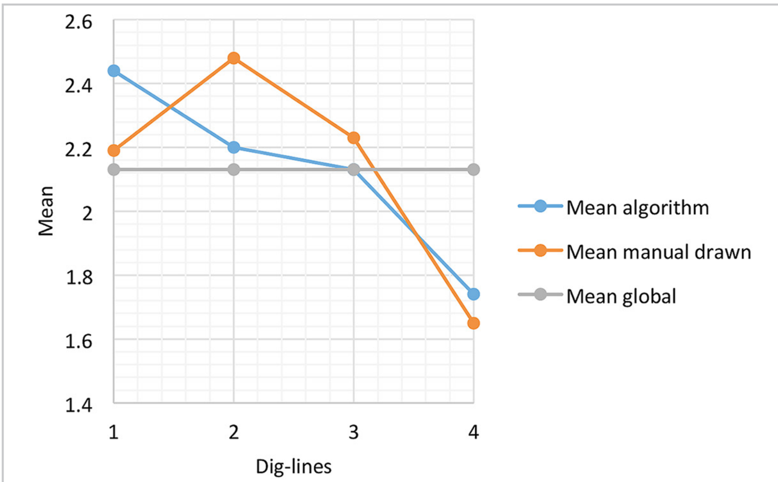

Figure 9 - compare the mean of the dig-lines designed by the algorithm, mean of the manually designed dig-lines, and the global mean.

Figure 10 compares the variance of the excavation lines designed by the algorithm, the variance of the dig-lines manually drawn, and the global average variance. Greater adherence to the global variance is observed in the dig-lines designed by the algorithm.

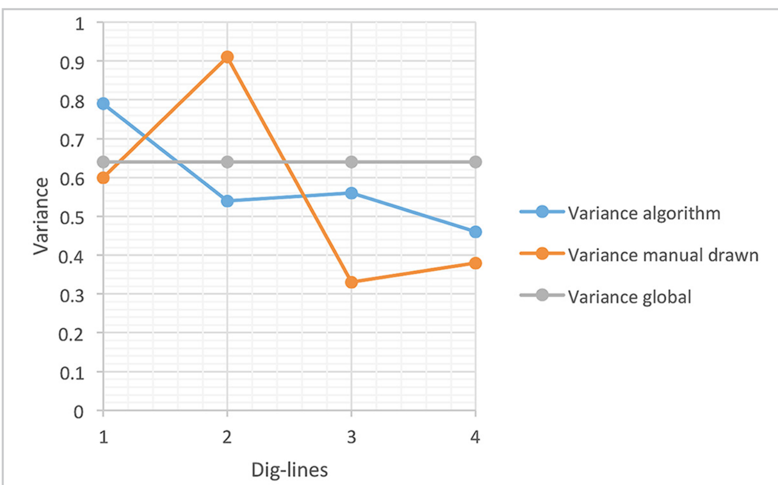

Figure 10 - comparison between the variances of the dig-lines designed by the algorithm, the variances of the manually designed dig-lines, and the global variance.

The time and effort used in the two cases are drastically different. Thus, the design of dig- lines with the algorithm is simple. As a prototype, it can be improved and implemented with more specifications, such as multiple chemical variables and attempt to make them maximum possible stationary.

4. Discussion

As seen from the results, starting from the same block model, it is possible to make variations in the short-term mine planning that lead to considerably different results. Another essential point to note is that this methodology is less time-consuming for short-term planning. The manual/traditional technique may take around 150 working minutes to do 4 subsets of 80 blocks compared to the one presented here, which takes 3 minutes 55 seconds to compute on an Intel I7 whit 2.6 GHz. Thus, even if there is no significant gain controlling of variations in the grades, there is still the time factor to be considered.

In addition, the proposed algorithm could easily efficiently perform an analysis in a multivariate case, where multiple variables should be considered simultaneously. Using geostatistical simulations, multiple input models would allow mapping of the uncertainty within the associated selected dig-line, which would probably be impossible when the dig-lines are defining manually.

The dig-lines that were generated in the benches by the algorithm search for the stationary histogram distribution of grades possible for the reference model, sequences the blocks in temporal order to achieve automatic optimization of the process. The generated results lead to selecting blocks where the average values are close to the reference. However, the probability distributions present slight discrepancies due to the conditions of geometric continuity, selection of blocks to dig-line adjacent to the seed points searched for by the algorithm. In the four dig-line with conditions of the example, the algorithm was limited to 80 blocks, so iterations obtained the same result because comparisons between the global histogram and four dig-line histogram are the same.

5. Conclusion

This article proposed a methodology to improve short-term mining planning by defining the optimal dig-lines and consequently defining the mining schedule which minimized the variation of the grades feeding the processing plant or the homogenization/blending piles. An algorithm was programmed in Python 3 used a Union-find data structure to select disjoint non-overlapping sets and genetic algorithms for automatization and optimization of short-term mining planning, targeting the reproduction of a reference-grade probability distribution.

It was verified that it is possible to optimize the selection of dig-lines for sequencing mining blocks, and also, to automatize routines that were commonly done manually. Additionally, the proposed technique allows the user to perform a faster analysis, considering a greater combination of technical parameters.

Although the study case is based on estimates in this case by kriging, it is believed that stochastic simulation models can also be used, thus making it possible to assess the uncertainty of short-term mine planning, which will be addressed in future studies.

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