Determination of Optimum Drawpoint Layout in Block caving

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Abstract

In a context of modern geostatistics, sequential Gaussian simulation has become a very popular technique to evaluate mining projects nowadays (Clayton V. Deutsch, 2015). Although realizations are used in different mining applications to solve specific mining issues for planning and production, there is still potential in the mining industry for using simulation. For instance, the usage of all realizations to generate optimal drawpoint spacing for a block cave is one of these potential applications.

There is a good amount of research related to block caving design, which includes studies about drawpoint spacing within the extraction level. Nonetheless, none of these studies considers the geostatistical simulation as instrument to obtain the drawpoint spacing for the block caving layouts. In this paper, an overall methodology based on Sequential Gaussian Simulation (SGS) to obtain the drawpoint spacing is suggested. The optimized drawpoint spacing is used to maximize the profit since the extraction layout is highly essential for the economics of block caving. This study is opening a new horizon for using "All Realizations All the Time" as a new approach to solve one of the trickiest elements of blocks caving.

1. Introduction

Mining companies around the world are constantly looking for forms to maximize the profit of their projects in surface and underground environments. For instance, among the underground operations, block caving has shown to be one of the most preferred mining methods in the last decade. The reasons are many, but one of them is because this type of massive mining is commonly used for the exploitation of deep and large low-grade material (Castro et al., 2012). Despite the fact that block caving is a very challenging mining method due to its complexity, this method is the most profitable among the underground types, so that block caves can be only compared with the open-pit mines, economically speaking. However, as mentioned above, block-cave mines depend on many constraints and parameters. Between these parameters, the drawpoint spacing is certainly the most critical one for designing the extraction layout in a block-caving project since this spacing causes important impacts in the final profitability of the mine. Several studies have been made about drawpoint spacing. However, none of them had used geostatistical simulation to solve this problem. Here is presented a proposed technique based on Sequential

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Gaussian Simulation, and using "All Realizations All the Time" to obtain the optimal drawpoint spacing.

To better understand this approach, a small study is developed; it provides a concise illustration to guide the reader for performing a design of an optimal drawpoint spacing that is a relevant feature in the extraction layout.

The study begins with an exploratory and analysis of the drillhole composites. After that, the variography is conducted. It is important to mention that, all the exploration, compositing, variography, and SGS modelling is performed by using the geostatistical tools of GSLIB catalog (Deutsch, C. V., & Journel, A. G. 1998). After having the explored data, a modelling process of the main variable (Cu) is developed. The modelling is performed by SGS. The simulation outputs consist of a group of 40 realizations that are imported to Gems (Geovia, Dassault Systemes) as 40 block models where the main variable is copper. Then, a following setting is performed in a block cave module, called PCBC. Several assumptions are considered as well as mining parameters has been set in PCBC-Gems. Parameters such as, development cost, mining cost, rock density, and others are considered as input data within PCBC-Gems. The PCBC module is used as the transfer function and generates a tremendous amount of important data that could be used for further analysis. From the generated data, the net value is the most important one to our purpose because the objective of this study is the search of the optimal drawpoint spacing to maximize the profit of a block-caving project.

The study results demonstrate that SGS is a very useful tool to obtain the optimal drawpoint spacing. Then, as mentioned above, the design of the best possible drawpoint spacing is a relevant task to maximize the profitability of any block cave mine.

2. Review of the Fundamental Principle of Simulation Applied to this Study

In modern geostatistics, the Monte Carlo Simulation (MCS) is a very well know computational algorithm; it relies on random samples to obtain some results. This algorithm is represented, in general, by the formulation of a problem with input variables, a transfer function, and the computed response variables which are assembled into a probability distribution (Clayton V. Deutsch, 2015), (Fig 1). Moreover, it is worth to mention that, the obtained distribution is also used to understand the uncertainty.

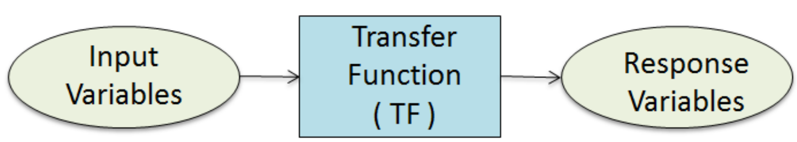

Fig 1. Monte Carlo Simulation concepts (Clayton V. Deutsch, 2015)

This paper illustrates a number of steps where the MCS is mimicked to explain how useful this method can be to solve mining-related problems.

First of all, the input variable (Cu) is simulated in a 20×20×15 grid, 40 realizations are obtained from SGS. For our case, the transfer function is an inner algorithm to calculate the net value ($) that is inside PCBC-Gems. It is important to mention that PCBC need several engineering and economical parameters such as mining and developing cost; and some assumption such as fragmental size, proposed drawpoint spacing type, etc. The transfer function converts the simulated copper values of every realization into response variables. In other words, one realization which is considered as one block model is converted into one net value ($), and then the 40 net values are organized in a distribution of response variables to obtain the mean (average) and the variance, for further uncertainty assessment. Then, to obtain the optimal extraction layout, several distributions need to be evaluated. Strictly speaking, each distribution belongs to a different layout.

3. Metodology and Experimental Work Flow

Further explanation of the concepts and results will be illustrated through a case study. The drillhole data was resampled from a confidential block model provided by Geovia, Dassault Systemes. In other words, a type of synthetic data is used throughout the study.

To show the proposed method, the present experiment is divided by three main stages, and they are explained as follows. First, a brief data analysis and a geostatistical simulation study are performed. Second, the setting of mining parameters and calculation are made in PCBC-Gems; PCBC is considered as the transfer function. Third, the results generated in PCBC-Gems for each of the layouts are processed in terms of net value to finally obtain the optimized block-caving layout at the initial extraction elevation.

Furthermore, the optimized block-caving layout is tested in four different extraction elevations in order to search for the best level of extraction based on the best net values.

4. Data Analysis and Variography

The first step includes the exploratory and the spatial analysis of the continuous data. As mention previously, the data was extracted from a former block model, and the copper (Cu) is the principal variable for a total of 55 drillholes. A 3-D plot of the drillholes is shown on the left side of Fig 2. While, on the right side, the 2-D location map of the composites is illustrated, this map has been generated with a program of GSLIB catalog (Deutsch, C. V., & Journel, A. G. 1998).

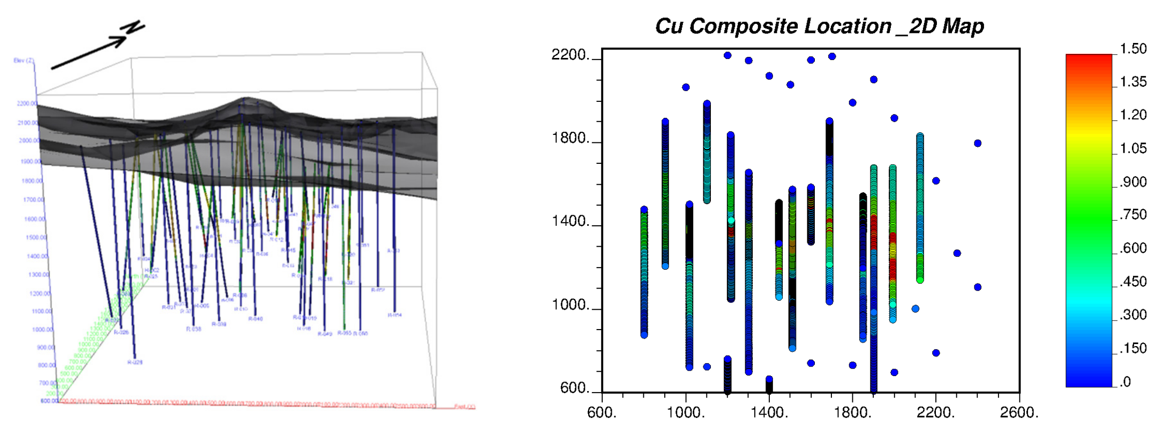

Fig 2. On the left, 3-D locations of drill holes, while a 2-D map of composites shown on the right

The drilling assays are composited to 10m. Each composite contains the x, y, z, copper(Cu), and lithology. After an exhaustive exploratory data analysis of all composites is performed, the global mean of the copper grade obtained is 0.229 % with a variance of 0.122. Fig 3 shows the global histograms.

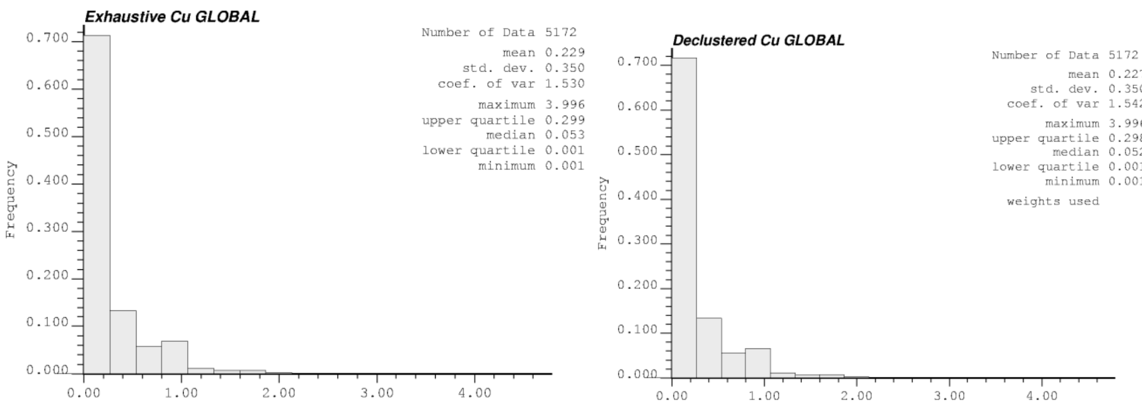

Fig 3. These two plots show the copper global histograms. The left plot is generated with no weights

The decision of stationarity is important before further statistical and geostatistical analysis is performed. Therefore, an implicit rock modeling is made with software based on Random Distance Function, shown in Fig 4. Then, the domain selection was decided based on the geological values of the data to simplify the process. The project is separated in two domains: Domain 1 and Domain 2. According to the geology of the area, Domain 1 is related to a porphyry intrusion, while the Domain 2 represents the country rock of the area, as shown in Table 1 and Fig 4.

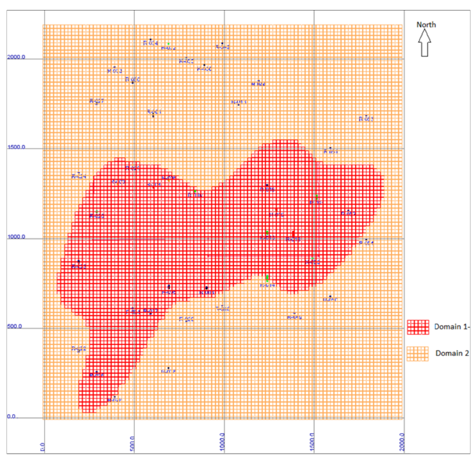

Fig 4. Two domains are Illustrated in a surface plot: Domain 1, and Domain 2

Table 1. Domain: two rock types and their codes

Rock Type	Domain Code
Intrusive	1
Country rock	2

Notice that, decision of stationarity is made for grouping the copper values within two distributions (domains). The domains are used to conduct further exploration and variography of composited data, so that the simulation modelling can be performed.

After the decision of stationarity is defined, cell declustering needs to be performed, ideally for the two domains. The DECLUS program (Deutsch and Journel, 1998) is used to get the declustering weights. The main idea is that values in cells with more data receive less weight than those in sparsely sampled places. To simplify the modeling process on the present study, only one cell size is chosen, for both domains. Fig 5 presents a plot that illustrates the possible cell sizes versus the declustered means. Then, according to the study data, the cell size 500×500 is elected.

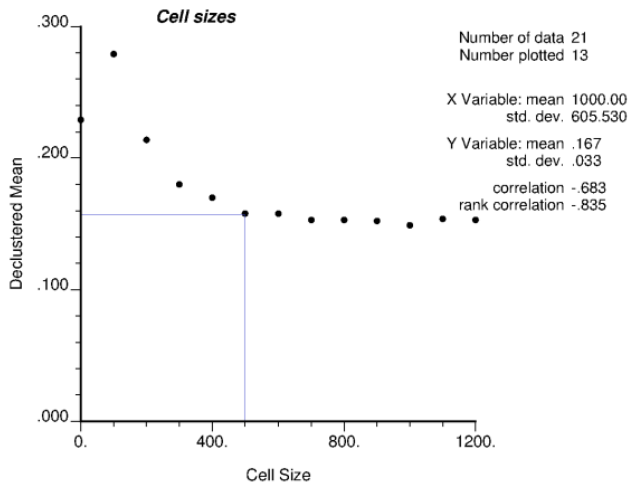

Fig 5. Cell size selection (500m x 500m) to generate the decluttering weights

Given the declustering weights, further histogram analysis over each domain is conducted. These plots are obtained with both declustering weights, and without them. As expected, histograms created with declustered weights show a small decrease in the mean and variance of copper values. Histograms of the two data-set distributions are shown in Fig 6. Plots present distributions with high-tail, looking like lognormal distributions. In both cases the tails contain few values. Those features are common in massive intrusive deposits, such as copper porphyry ones, and where the country rock (Domain 2) contains some mineralization. Cumulative plots are shown in Fig 7, thus the domain 2 clearly show that almost 80 percent of its copper values are close to zero. The weighted mean of the copper grade obtained for Domain 1 is of 0.42% cu with a weighted variance of 0.16, while the weighted mean of the copper grade obtained within Domain 2 is 0.04% with a weighted variance of 0.01.

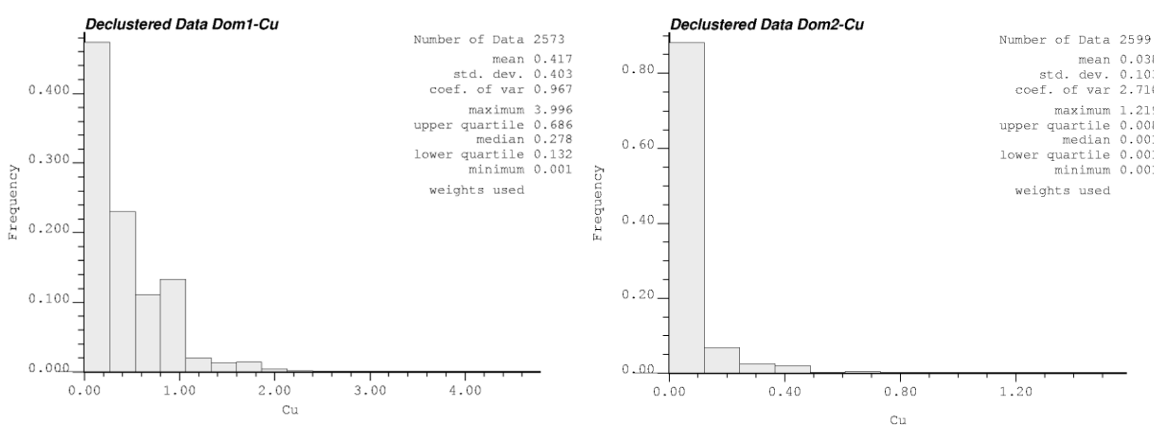

Fig 6. Histograms of the two domains, using the weights

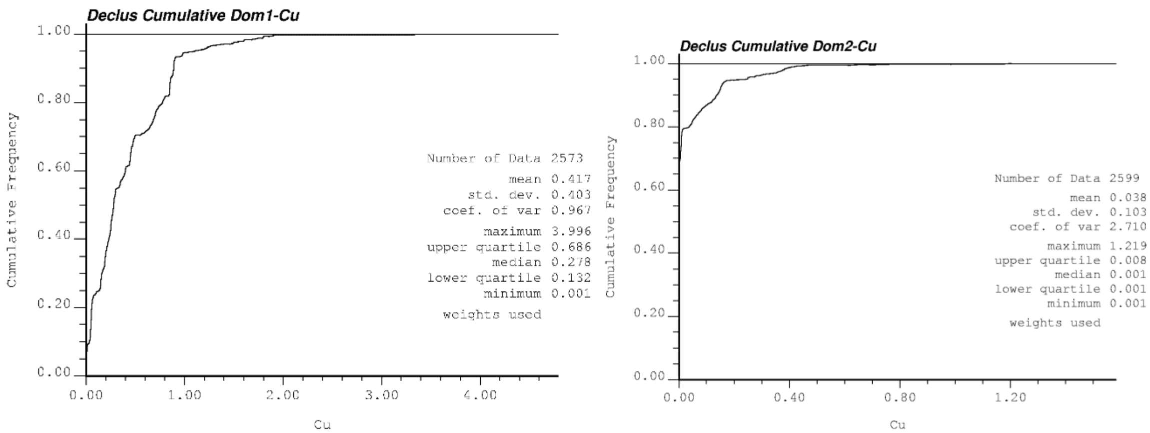

Fig 7. Cumulative plots for the two domains

Geostatistical simulation will require not only the declusted set of data, but also this data will need to be transformed into normal score units. Hence, our data is transformed to normal score values using the NSCORE program (Deutsch and Journel, 1998). The two declustered and normal scored distribution are shown in Fig 8.

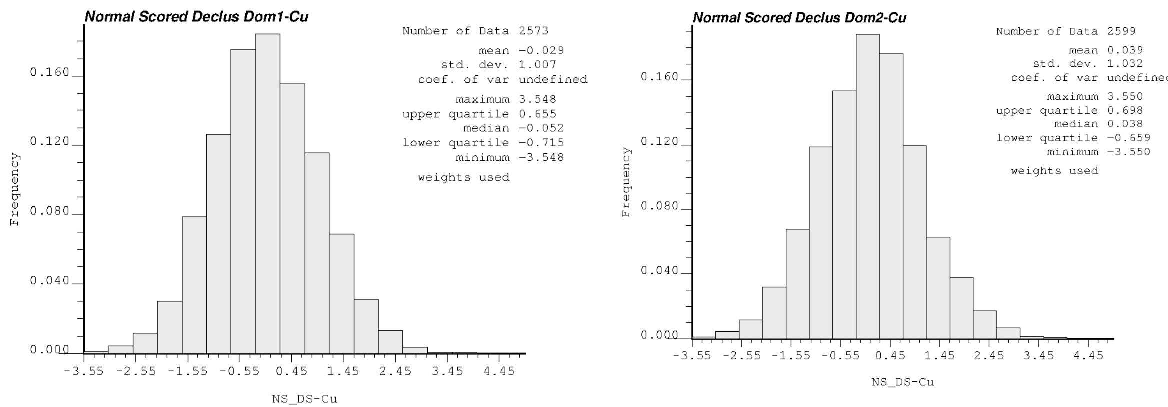

Fig 8. Two normal scored histograms for the two domains.

Modeling the spatial continuity of the rock indicator and copper grade using variograms is an essential step before the SGS is performed. Variograms are the common spatial measure of continuity which shows the variability of grades with distance. This study includes two types of variogram modelling. One of them is the indicator variogram modeling, and the second one is the continuous variogram modeling. The experimental and fitted variogram models in major, minor and vertical directions are displayed in Fig 9.

For the continuous variable, all the directional experimental variograms have been calculated using the GAMV program (Deutsch and Journel, 1998). The VMODEL program was used to fit the anisotropic variograms. These models contain two nested spherical structures, and the major and minor directions are 90 and 0 degrees respectively.

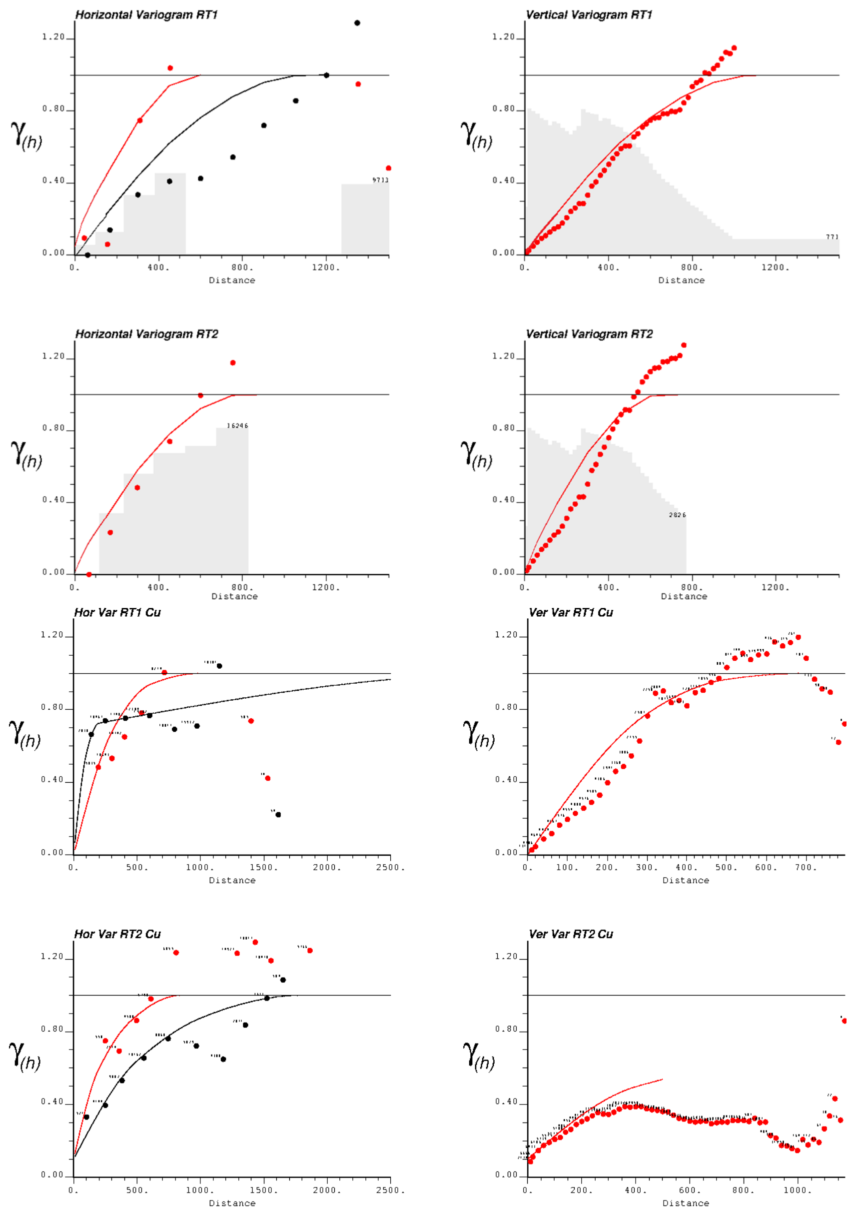

Fig 9. Four fitted Indicator variograms on the top, and four fitted continuous variograms at bottom

5. Sequential Gaussian Simulation

Besides the deterministic implicit modeling of rock types that has been performed and shown at the beginning of this paper, a rock modeling of sequential indicator simulation(SIS) has been conducted (Figure 11, on left). The SIS model is used to regulate the continuous data in order to generate forty simulated realizations with the software of sequential Gaussian simulation of the GSLIB catalog (Deutsch and Journel, 1998). Then; forty realizations are performed to obtain the input values for PCBC. These simulated realizations are considered to be equally probable. The process to perform the SGS is explained briefly as follow:

1. Determination of the correct grid is defined; it will be according to the horizontal and vertical continuity. A total of 1210000 blocks make the model framework. The grid

dimensions are of 20 meters in X axis, 20 meters in Y, and 15 meters in Z. The origin of coordinates is: X = 600m, Y = 100m and Z=600m.

2. After declustering and normalization, data is used as the main input within the sequential Gaussian simulation software of the GSLIB catalog (Deutsch and Journel, 1998).
3. To generate multiple conditional realizations of the main variable (Cu) within the Sequential Gaussian Simulation software (sgsim), a variogram model is needed. It is worth to mention that, the sgsim software is one of the most commonly applied geostatistical simulation algorithm that is used in the mining sector. Fig 10 illustrates two plots of realizations that are performed at level 1150; they are samples of the SIS model and the SGS model respectively. They both belong to realization 1, slice 74 (level 1150).
4. To validate the reproducibility of the SGS model, the reproduction of histograms is performed (Fig 11). Results display a good reproduction for domain 1 (intrusive). However, domain 2 shows an acceptable reproducibility, but it is not as good as domain 1. This is happening probably because the boundary is soft, and the mean and variance of the reference original data seems to be affected by some of the high copper values.

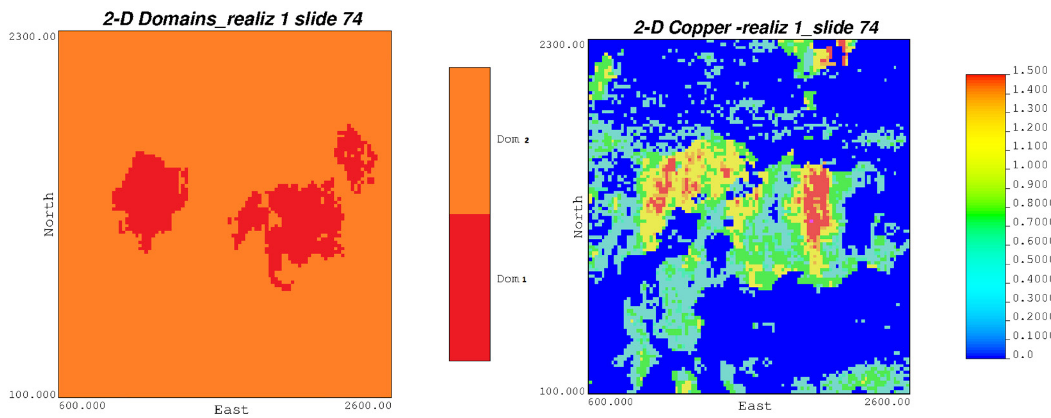

Fig 10. A SIS realization (left) and a SGS realization (right). They both belong to realization 1; slice 70 at the 1110 level

6. Setting the PCBC Parameters and the Transfer Function

After the geostatistical simulation modeling is performed, and a group of forty realizations are obtained, the setting of the transfer function is started. These realizations are considered to be equally probable block models of copper. Then they have been imported to a mining software, called Gems. To process these forty realizations inside the PCBC module, several mining assumptions and parameters need to be considered. Tables 2 and 3 show the essential assumptions and parameters that need to be taken into account inside PCBC before any calculation is made.

The imported copper models are manipulated in Gems. Then, additional values such as rock, density and percent of fines are added to these models. Once the 40 block model is completely ready to be used, the PCBC module is set. It is important to mention that some assumptions are made based on previous studies and the authors' experience, look at Table 3.

The PCBC journey begins with the setting of some assumptions. The first assumption is taken from the averaged fragment size, where rock is moderately fractured. Then the average size is assumed to be 0.5-1 m^3.

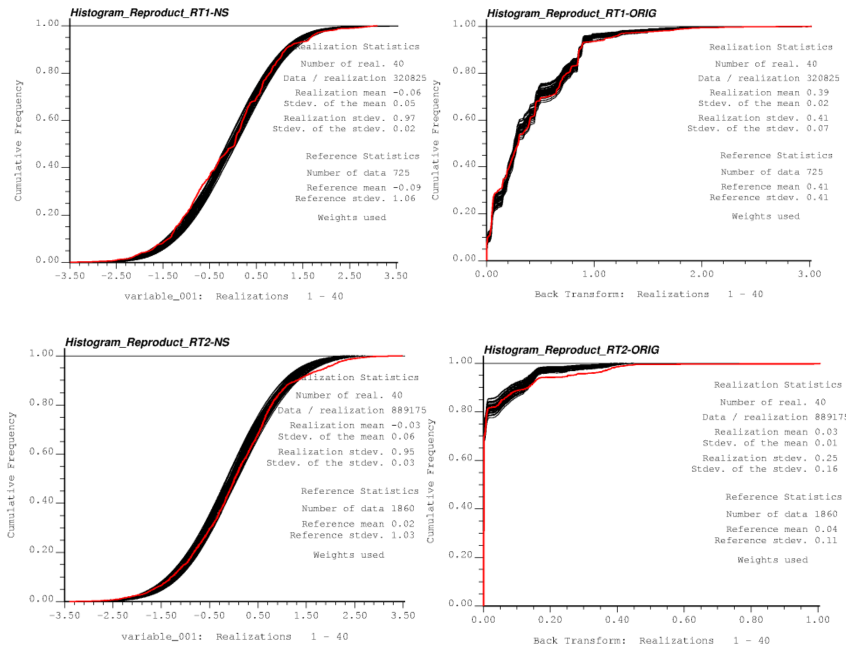

Fig 11. Histogram reproductions for Domain 1 and Domain 2, for the original and NS data

Table 2. Three drawpoint layouts used to find the optimal net value

Layout type (Herringbone)	spacing across major pillar (m)	spacing across minor pillar (m)	Description
20×10	20	10	The distance between drawpoints within same bell is 10m
20×15	20	15	
20×20	20	20	

Table 3. Relevant mining parameters and assumptions used within PCBC

Parameters & Assumptions	Value	Units	Description	References
% of Fines (ore&waste)	30	%	Based on a model of fines	Diering, T., (2013)
Density	2.5	kg/cm3	Average density for the orebody	Authors (2016)
HIZ	100	m	Height for interaction zone	Diering, T., (2013)
Swell factor	1.2	-	Stablish by experience	Authors (2016)
HOD_MAX	500	m	Maximum Height of Development	Diering, T., (2000)
HOD_MIN	30	m	Minimum Height of Development	Diering, T., (2000)
Discount Rate	0	%	It is assumed 0 % discount rate	Authors (2016)
Initial Elevation	1150	m	Initial Elevation of extraction	Geovia-Footprint Finder
radius of drawcone	5	m	Based on fragment sizes	Laubscher, D (1994),
layout type	-	H	Herringbone type	Ahmed, H. et al., (2014).

Consequently, the radius of the drawcones should be set to 5 meters. After that, the second assumption that needs to be considered is the initial level of extraction which is assumed to be 1150m. It worth to mention that, the extraction level has been obtained previously by running the "Footprint Finder" located amid the tools of PCBC-Gems. The assumptions and the main variables are essential for starting with the calculation of the responses within PCBC as well as other parameters that need to be completed to guarantee the successful usage of the transfer function into the PCBC module.

After the previous delineation of the initial footprint level, a number of sensitivity studies are performed. Therefore, a narrowed number of extraction layouts have been elected; In addition, a summary of other assumptions and parameters is made. In addition, the information of development cost for the extraction layouts is shown in the Fig 12 and the Table 4. The herringbone layout type that is used throughout the entire study.

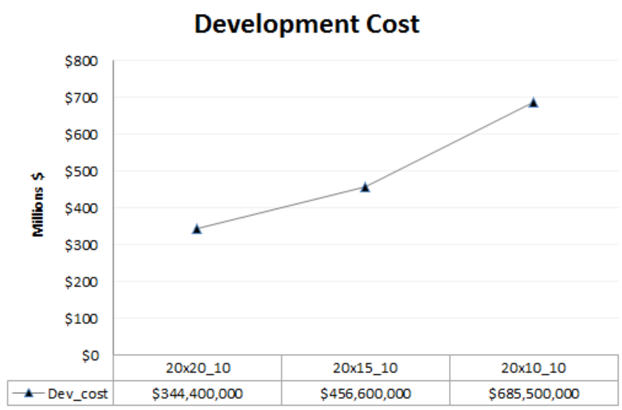

Fig 12. The development cost for the three extraction layouts

Table 4. Mining and development cost for the three extraction layouts

Block Caving Layout(Herringbone)	Mining Cost ($/tonne)	# of Drawpoints	Development Cost ($/drawpoint)	Total development Cost ($M)
20×20	7.0	2296	150,000	344.4
20×15	9.3	3044	150,000	456.6
20×10	13.9	4570	150,000	685.5

7. The Optimal Drawpoint Spacing within the Initial Footprint

The PCBC-Gems module does not only allow a numerical model to be set up, but also allows the columns above the drawbells to compute the minable reserves (Fig 13) in a variety of scenarios. Each extraction layout is one different scenario (Table 2). In this study, the PCBC generates 40 different responses for each of the three scenarios, and the final results that is evaluated in this paper are in terms net value ($). The main idea is to run each of the 40 realizations by three times. These three times represent the three different drawpoint spacing that is shown in Table 2 and Table 4. They are 20×10, 20×15, and 20×20. In other words, the 40 realizations obtained from the previous simulation are used in PCBC to determine 40 response variables for the three types of extraction layouts.

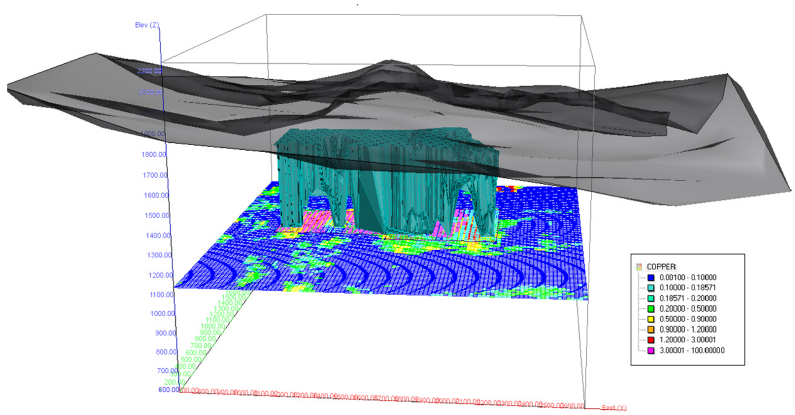

Fig 13. Calculation of minable reserves by PCBC. The optimal drawpoint layout and the best level possible are shown in here.

Fig 14 illustrates the response variables for these three scenarios, 20×10, 20×15, and 20×20. These response variables are plotted on the left side of Fig 14, where three distributions are shown in terms of net value ($M). Notice that the averaged net value obtained from the distribution at layout "20×15" seems to be the optimal one. Furthermore, the right side of Fig 14 shows a ranking of the best values for each layout. 88 % of the maximum values are obtained for layout "20×15". It is worth to mention that; further uncertainty assessment can be performed with this data.

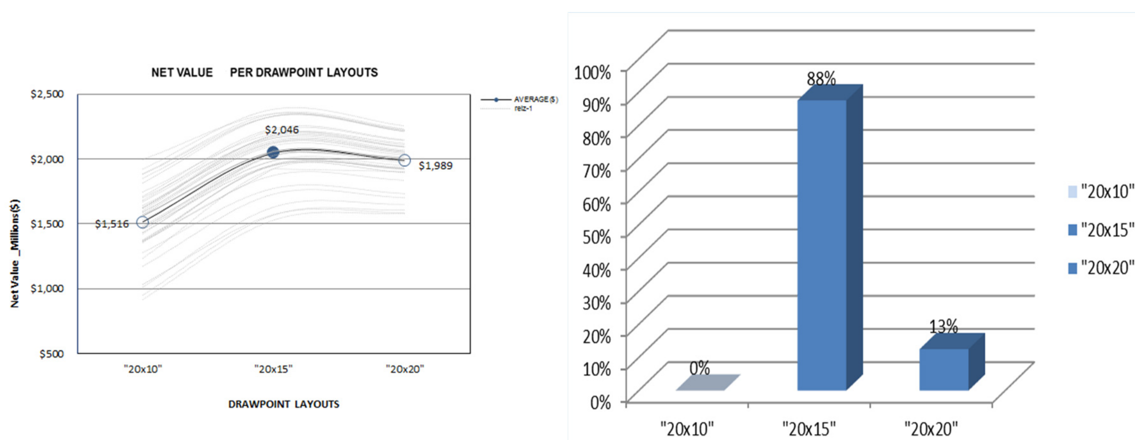

Fig 14. On the left, the forty net values for the 3 layouts, and the ranking of best results on the right

Fig 15 shows a histogram of the distribution at layout "20×15" which appears to present the most optimal net value; the mean net value is around 2046 million with a standard deviation of 218.

8. The Best Level of Extraction Based on the Optimal Drawpoint Spacing

Once the optimal drawpoint spacing is completed, a complementary evaluation of the best extraction level is made with PCBC- Gems. The layout “20×15”, now, is used to find the best elevation of extraction. Then, this level of extraction will be used in a second round of the optimization process. In fact, only one round has been shown in this paper. To find the best level of extraction based on the optimal drawpoint spacing, an evaluation is conducted within the following four elevations: 1030 m, 1090 m, 1150 m, and 1180 m.

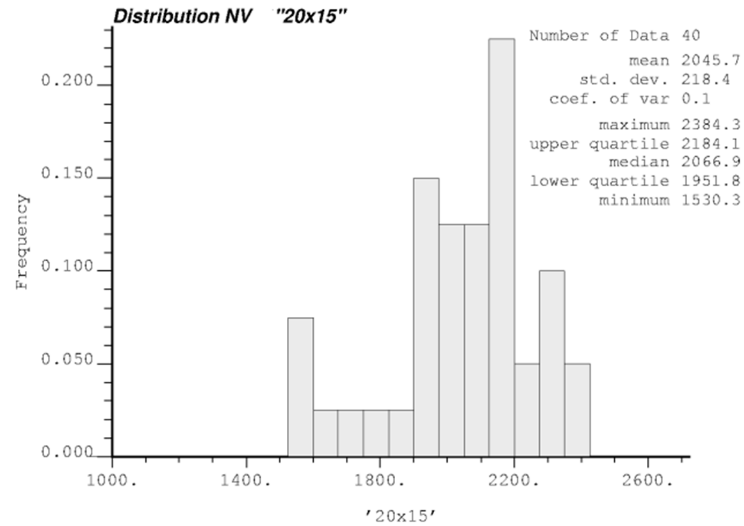

Fig 15. The distribution of the net values ($M) for the optimal extraction layout

These elevations are chosen arbitrarily based on the author's experience. However, the ideal elevation should be proportional to the block sizes.

In the left side of Fig 16 is shown the results of the calculation performed in PCBC-Gems where the best average of the net values appears to be at the elevation 1150 m. Around 55% of the best responses (net values) are at elevation 1150 m. However, 45% of best net values are at elevation 1090 m; this ranking of results is illustrated on the right of Fig 16. Furthermore, Fig 17 shows a histogram of the distribution at elevation 1150 m performed in the optimal layout; the mean net value is around $2046 M with a standard deviation of 218.

9. Results and Discussion

Among the three layouts which were evaluated in this study, the "20×15" appears to show the optimal net value; the mean of the net values is around $2046M with a standard deviation of 218. We need to remember that the initial evaluation within PCBC-Gems is performed at an extraction level (footprint), and It is relevant to mention that this initial extraction level has been obtained automatically by running the Footprint Finder of the PCBC-Gems. The methodology of this paper also proposed a complementary evaluation of the best level of extraction using all realizations; in this case, the optimal drawpoint spacing needs to be fixed. From the response results of the calculation performed in PCBC-Gems, the best average of the net values appears to be at the elevation 1150 m with 55% of best responses (net values) in where the mean net value is around $2046M with a standard deviation of 218.

The study results demonstrate that the SGS is useful to obtain an optimal drawpoint spacing based on realizations. This paper certainly explains, in simple steps, how to generate the best possible drawpoint spacing for a specific "extraction layout" of a block caving mine. It is also explained here, the results of additional evaluation to obtain the best level of extraction using a fixed drawpoint spacing. In other words, given the drawpoint layout of "20×15" as the optimal drawpoint spacing at the initial level of extraction, a complementary evaluation of elevation is performed. This new elevation would be used to perform further optimization of the drawpoint spacing following the previous steps.

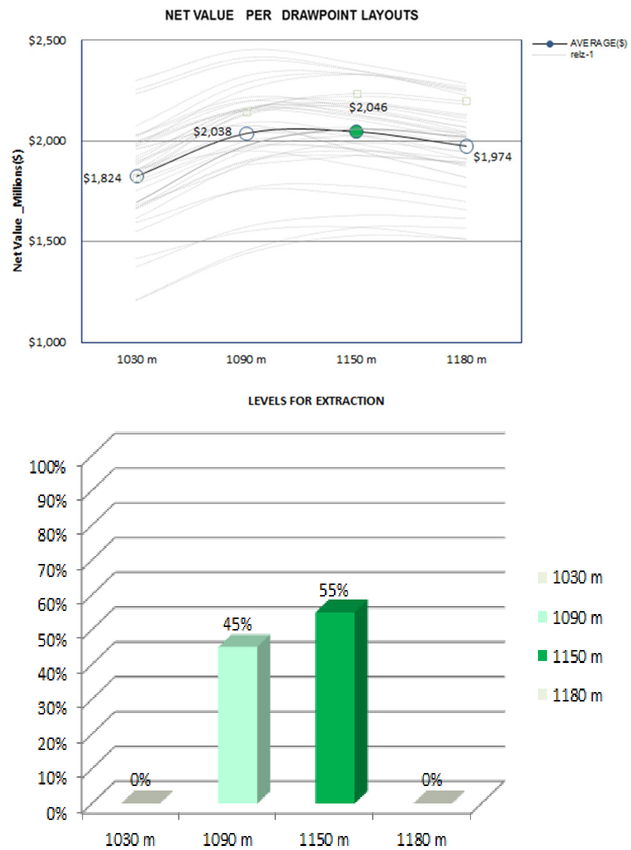

Fig 16. Responses of net value for the forty realization, and the ranking of results for the four levels

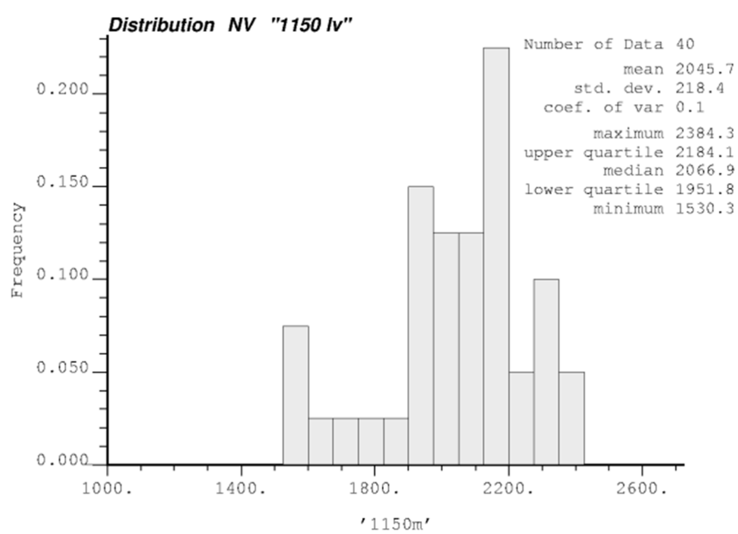

Fig 17. Histogram with the distribution of the net values ($M) for the best elevation of extraction

10. Conclusion

Overall, the optimal drawpoint spacing within the extraction level will help to achieve the production targets of a mine. For instance, tonnage, grade, and consequently the profit of the block-cave mine. As explained in the introduction, this type of mining is undeniably complex since they depend on several assumptions and parameters related to their geological and technical constraints.

However, there are few essential features that need to be considered carefully because this work illustrates a completely new approach to solve one of the trickiest features of block caving. In fact, this paper is opening a discussion about a new application for simulation in the mining context, using “all realizations all the time”. This paper explains also a comprehensive workflow to maximize the profitability of the block caving mines. The maximization of the profit would be based on the optimal drawpoint spacing within the best level of extraction. Nonetheless, further complementary studies of geostatistical simulation and uncertainty assessments should be done for block caving, in the future.

11. References

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