Development of a geostatistics methodology for planning of SECIL-Outão's quarries

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Abstract

The way a mineral mass is explored depends heavily on the quality of its resource estimation. This study focuses on two quarries, composed of limestone and marl, which are managed by SECIL. The company uses a geochemical model made in 2006 based on the inverse squared distance to estimate the mineral contents in the central mass of the two quarries in Outão. The main goal of this study is to build a new model, based on geostatistical estimation and kriging. Utilizing *Surpac* as the modelling software, which offers a three dimensional view of the different mineral densities throughout the quarry in a continuous domain due to the kriging process. The database used consists of 818 samples from drilling powder, collected during blasting procedures in the quarry, and bore drill holes. The results show a dependence on some of the variables, allowing for a correlation to be drawn when modeling the variograms. Afterwards, a block model of the quarry can be made, where the several variables can be viewed block by block for easier access.

This approach results in a more precise model of the mineral content in the quarry's central mass, enabling a more efficient planning of the resource extraction and optimizing the cement production process.

Keywords: geostatistics; kriging, optimization engineering, 3D modeling

Introduction

In times of economic recession, geological resources play a key part in the recovery process and, because they are primary raw materials, they are needed in the production of new goods, which add value to the economy.

As common knowledge, cement originates from physical and chemical processes that utilize four fundamental raw materials: limestone, marl, sand and pyrite. According to the study Sectores Portugal, published by Informa D&B, cement exportations have grown 30% in 2013 since the last year, a total of 133 million Euros. For a continued economic growth, the resource exploitation needs to be optimal, as the production of cement depends directly on the resource availability. SECIL is one of the companies responsible for this growth in export rates, and this study will focus on the quarries they manage in Outão.

The main goal of this study is to model the central mass of the SECIL-Outão quarries, composed mainly of limestone and marl, using drilling powder collected since 2008 and bore drill holes made in 2006. The intention of this new model is to improve and upgrade the company's knowledge of their mineral reserves. Currently, only a geochemical model of the central mass exists, and that model is based on the inverse squared distance method. This model doesn't have a correct resolution of quarries' layers. The layers are oriented 45º E-W and with this model is impossible to conclude about this subject, as can be seen in figure 1, which leads to a bad exploitation plan. Thus, with this work, the company will have access to a geostatistical model of the quarries, made with block kriging. This allows the estimation of the oxide grades by unitary rock removal blocks, which is useful for further exploitation planning. This model will be made with one of the world leading geostatistical software: *Surpac*, by *Geovia.*

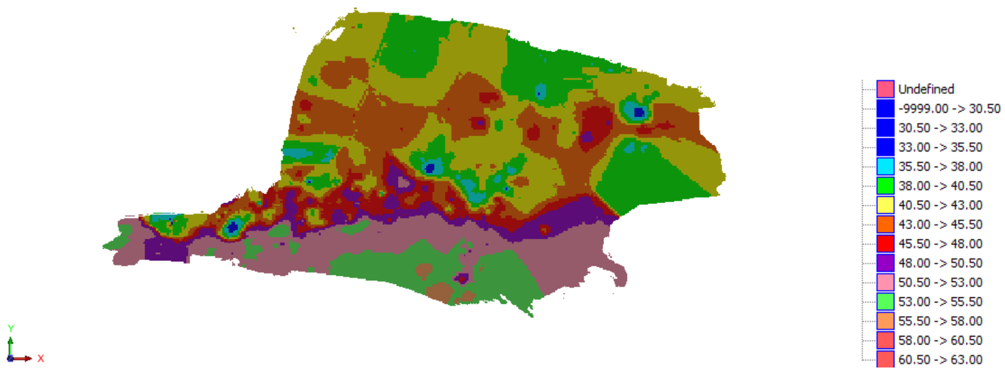

Figure 1 - Current modeling of the quarries, made with inverse square distance

The geostatistical analysis is based on a set of observations that constitute samples. Those observations are used to infer on the properties of the spatial phenomena being studied and to represent the population from which the sample was extracted (Yamamoto & Landim, 2013).

Geostatistics try to spatially characterize variables by studying their distribution and spatial variability, along with their uncertainty. The spatial phenomenon is the set of all the possible values of the variable in study, which defines the distribution and spatial variability of that variable in a 2D or 3D domain. It represents, statistically, the population that is the set of values from which the sample can be extracted (Yamamoto & Landim, 2013).

Methodology

The success of any mining enterprise depends on the relevance of the mining reserve estimation, made from variables (such as thickness, density, grade, etc), and experimentally measured in mine deposits. Any assessment based on sample data is subject to error. The true value of the grade or any other variable of interest will be known only when the exploitation of the deposit is initiated. Therefore, the best estimation of grades and mine reserves is the mains objective of the professional work of evaluation. That aim is achieved following a logic sequence of evaluations, which allows the delineation of the ore body, as well as the selection of an appropriate method to calculate the mineral reserves (Yamamoto, 2001).

Thus, the reserves evaluation work begins with sampling, chemistry analysis for further integration into the software to be used, creation of a block model (adequate tool for estimation) and geoestatistic modeling (Elias, 2013).

In order to be carried out the central mass' modelling, it was necessary collect information of analysis of the drilling powder. The samples consist of geographic information (X, Y, Z coordinates), chemistry information (grade) and mining information (length of the drill hole and dip). They were collected since 2008 until 2013.

The organization and evaluation can involve such as fifty percent of the time needed to develop a geostatistic estimation. The main aspects of data estimation system are:

(i) Development of a file and an input of the data;
(ii) Edition of the data;
(iii) Quantification of the data quality;
(iv) Grouping of the data according to the geological domain and sample support;
(v) Univariate analysis (histograms);
(vi) Bivariate analysis (correlação);
(vii) Special patterns and tendencies

(Sinclair & Blackwell, 2002)

Although the multivariate analysis is important to a statistic and geostatistic study, it was not performed due to the fact of existing too many samples, sufficient to take conclusions only with the univariate and bivariate analysis.

During this work, was developed two data bases: one with all the data and another one only with the marls data (North of the central mass). The last one is the most important to perform the conclusion of this work, because the central mass is marly and the estimation for unitary block will be important to plan the exploitation on the marl. Even so, the joint analysis of the two data bases is predominant to a correct analysis of the problem.

For choosing the block model to use, it was made sixteen tests, with different groups of coordinates, in order to obtain the best efficiency, combined with the biggest number of blocks. The chosen coordinated take into account tests which dimension number is submultiple of 20 or 15. The test that provides best efficiency and biggest number of blocks is the one which block size is: $X_1 = 5.00$, $Y_1 = 5.00$, $Z_1 = 2.50$ and with this sub-block size: $X_2 = 2.50$, $Y_2 = 2.50$, $Z_2=1.25$.

Statistics

To properly estimate the contents being studied, a statistical analysis must be made. Classical statistics indicate parameters like the number of samples, sample value range, average value, median, variance, standard deviation, correlation coefficient and other statistical indicators. The correlation coefficient between the different oxides is analyzed in table 1.

Table 1 – Correlation coefficients (all samples)

TOTAL	CaO	SiO_2	Al_2O_3	Fe_2O_3	MgO
CaO	1.00	-0.93	-0.88	-0.84	-0.43
SiO_2	-0.93	1.00	0.92	0.85	0.34
Al_2O_3	-0.88	0.92	1.00	0.95	0.16
Fe_2O_3	-0.84	0.85	0.95	1.00	0.16
MgO	-0.43	0.34	0.16	0.16	1.00

The correlation between calcium oxide (CaO) and the rest of the variables is negative. This shows an inverse relation between the presence of CaO and other oxides, with the exception of MgO, that is sufficiently uncorrelated from the other variables to be considered relevant.

The remaining oxides (SiO_2; Al_2O_3; Fe_2O_3) are strongly correlated between each other, showing a strong relation in the presence of these three oxides. Once again, magnesium oxide remains very poorly correlated, sometimes showing correlation coefficients of 0.16 which is representative of clearly uncorrelated variables.

By analyzing each oxide grade in a histogram, it is possible to determine characteristic behaviors in the amount of samples with certain concentrations. This is the case of CaO, which has two distinctive spikes in concentration the first spike is centered in 41% grade, and the second on is centered in 53% that correspond to marl and limestone respectively. The two types of rock masses can be clearly seen in figure 2. For the purpose of this this study, we will be focusing on the marl rock mass, since the central mass of the quarry, which is the subject of study, consists mainly of marl.

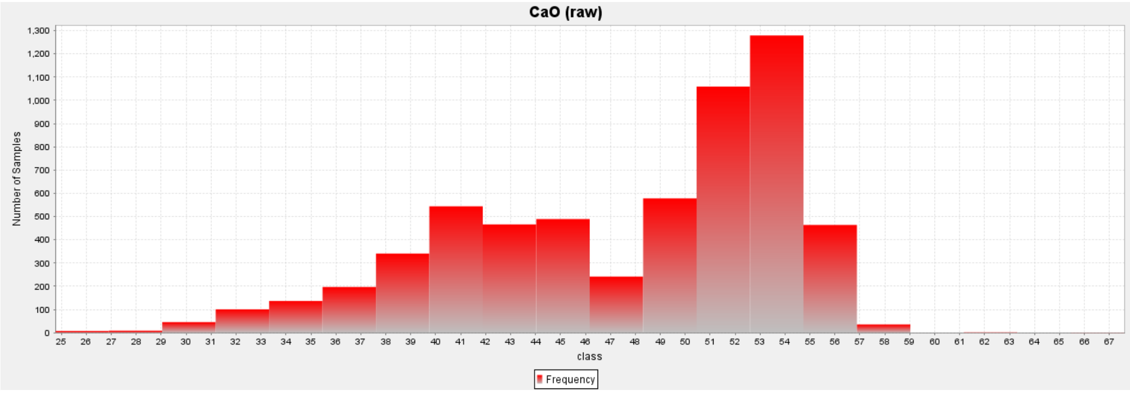

Figure 1- CaO grade histogram

For the study of the oxides in the marl rock mass (table 2), the samples considered will have a restriction on the CaO grade (35.00%<CaO<47.90%) which corresponds to the concentration range of calcium oxide in marl.

Table 2 – Correlation coefficients (marl samples restriction)

MARGA	CaO	SiO_2	Al_2O_3	Fe_2O_3	MgO
CaO	1.00	-0.68	-0.56	-0.49	-0.24
SiO_2	-0.68	1.00	0.73	0.53	-0.06
Al_2O_3	-0.56	0.73	1.00	0.79	-0.34
Fe_2O_3	-0.49	0.53	0.79	1.00	-0.25
MgO	-0.24	-0.06	-0.34	-0.25	1.00

Restricting the samples to the ones considered marl, CaO grade (35%<CaO<47.9%), the correlation between the oxides becomes even stronger when compared to the coefficients in table 1.

The next step in the statistical analysis is the modeling of variograms, which are needed as parameters for the kriging estimation. Two groups of variables were made to model the variograms, Group 1: CaO (D1) and SiO_2 (D2); Group 2: Al_2O_3 (D3) and Fe_2O_3 (D4). (D5) is for MgO, which is irrelevant for the study.

The parameters utilized for the total samples and the marl samples are represented respectively in table 3.

Table 3 – Sample parameters for variogram modeling

		Variogram				Anisotropy Factores	
TOTAL	**Variance**	**Model**	**Range**	**Sill**	**Nugget Effect**	**Major/Minor**	**Major/Semi-major**
D1	42.95	Spherical	450	32.95	10.00	2.70	2.70
D2	30.07	Spherical	450	23.07	7.00	2.70	2.70
D3	8.42	Spherical	450	7.42	1.00	4.06	2.36
D4	2.81	Spherical	450	2.16	0.65	4.06	2.36
D5	1.52	Spherical	450	1.47	0.05	1.00	1.00
		Variogram				**Anisotropy Factores**	
MARL	**Variance**	**Model**	**Range**	**Sill**	**Nugget Effect**	**Major/Minor**	**Major/Semi-major**
D1	9.40	Spherical	200	6	3.4	7.23	1.00
D2	11.64	Spherical	250	7.43	4.21	2.36	1.00
D3	4.05	Spherical	450	2.97	1.08	3.42	1.00
D4	1.64	Spherical	250	1.54	0.10	1.39	1.00
D5	2.66	Spherical	450	2.51	0.15	3.20	1.00

In this analysis, a spherical model was chosen to best fit the sample distribution. The range for all samples, although equal when considering all variables, is modified for marl samples due to their spatial distribution being concentrated in a smaller volume, which is the marl section of the quarry.

Kriging

According to (Vieira & Grego, 2000)and (Thompson, 1992) kriging provides improved interpolation estimates. Block kriging estimates the values for each block based on a weighted average of the sample points, selected according to ellipsoid scanning centered on the block. With the correct attributes identified (sample database, variogram model and anisotropic ellipsoid) the kriging estimation is now possible. The resulting models are shown for modeling the CaO concentration distribution for the whole quarry and for the CaO distribution when considering the marl samples in figures 3 and 4 respectively. Both images represent a vertical view of the quarry (i.e. viewed perpendicular to the ground)

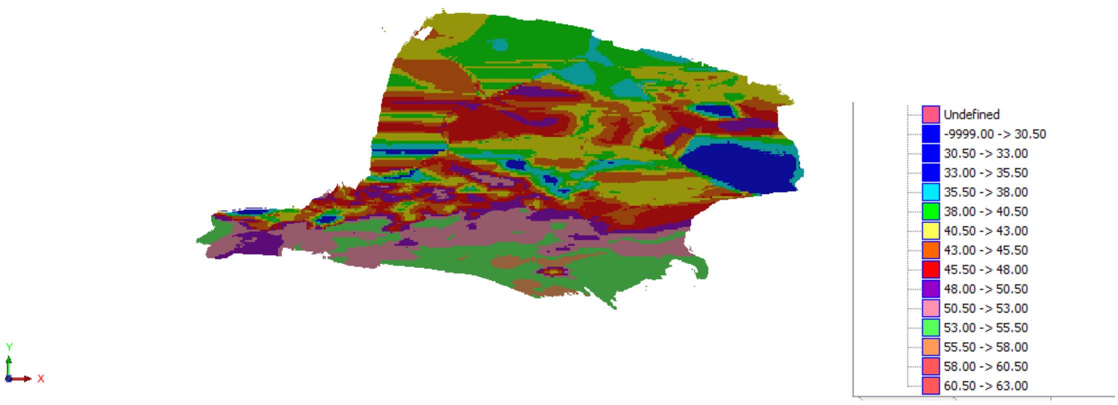

Figure 2 – CaO distribution throughout the quarry (XY plane)

In figure 3, there are two predominant values for the concentration of CaO. This was already expected after analyzing the histogram in figure 2, where there were two spikes in CaO grades representing limestone and marl. It is possible to understand that the layers of the quarries are oriented 45º E-W. The volume of rock for each grade of CaO can be plotted to illustrate the amount of marl and limestone present in the quarry, and is shown in chart 1.

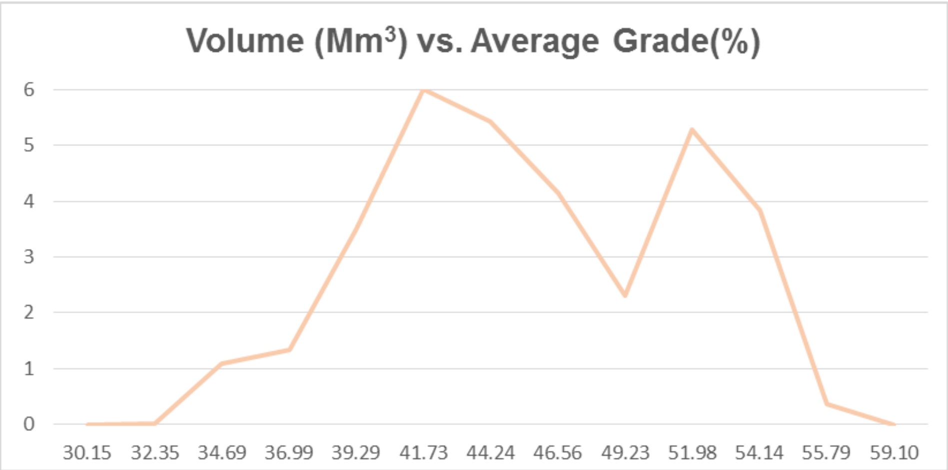

Chart 1 – Rock volume per CaO grade

With kriging, it is also possible to see the spatial distribution of those rock types, and identify the marl section.

By selecting only the marl samples, a new estimate of the different oxides in the quarry can be made. The kriging for CaO in the marl samples is shown in figure 4, only for the marl quarry, opposed to figure 3 that shows both the limestone and marl quarries.

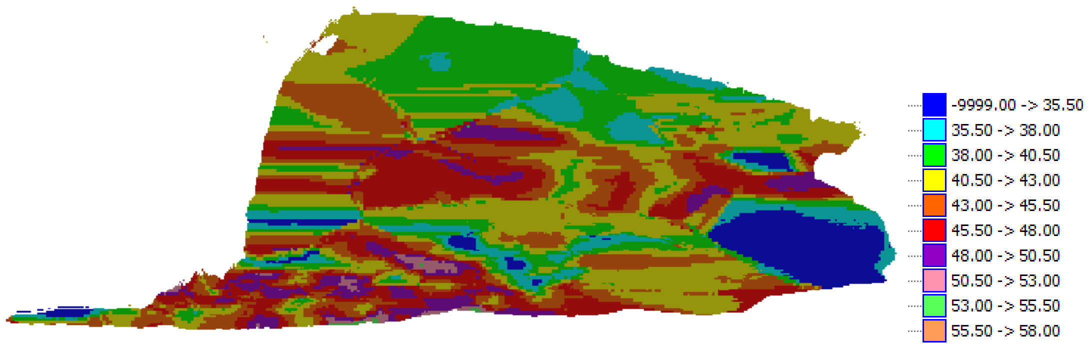

Figure 3 – CaO distribution throughout the marl samples (XY plane)

The kriging done hints at three different types of marl: with grades around 39%; 41%; 43% and 46%. This can also be seen in Figure 4 as clusters of marl with different CaO grades in regular shapes.

The different kriging estimates done for SiO_2, Al_2O_3 and Fe_2O_3 are all very similar, as was expected due to their high correlations.

Conclusion

The procedures presented in this thesis aim to improve the mining techniques with the aid geostatistics, by crossing as much information as possible through different surveys.

The estimations made are compatible with those already observed in the quarries, which is a strong validation of the estimated model. This estimation work is important not only in the discovery of new lithologies, as it is commonly used, but also in the improvement of the precision of already existing ones.

Kriging allowed evidence of the orientation of the layers for 45º, which suggests a correct estimation, giving an upgrade to the enterprise. Thus, it is possible to ensure a good planning of the extraction of limestone and marls, taking into account the quality objectives of the raw materials.

An improved model of the quarries' contents provides a more complete knowledge of its mineral availability which contributes to a better cement production planning and scheduling leading to an overall increase in production efficiency.

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