MINING THE OCEAN FLOOR – MANAGING GEOLOGICAL UNCERTAINTY

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ABSTRACT

As land resources decrease, commodity prices increase, and technology evolves, deep sea mining is becoming a viable alternative to meet the increasing demand for minerals. Successful deep sea mining operations are built on sound identification of the resource, proper selection of equipment, a thoughtful production plan, and good project management. These four key activities can be further optimized by analyzing how the spatial variability and uncertainty of the ore body properties impact the final mining operation. To address this problem, IHC Merwede is in the process of developing a risk quantification framework in the context of deep sea mining, which makes use of state of the art geostatistical simulation methods and transfer functions to quantify geological uncertainty and translate it into decision or project risk.

The paper introduces the Local Average Subdivision method (LAS) for generating simulated models of the deposit and presents a new extension to incorporate point measurements of geotechnical or ore grade properties. Due to its computational efficiency, the presented method is suitable for simulating largely extended sea floor deposits. The second part of the paper illustrates, through example case studies, the significant benefits of a risk based approach which translates geological uncertainty into financial or operational performance indicators. In particular, the focus is on assessing financial project risk and on the design optimization of the deep sea excavation equipment by analyzing cutting forces, specific energies, and power requirements.

KEYWORDS

Geostatistical simulations, Local average subdivision, Spatial variability, Geological uncertainty

FUTURE NEED FOR DEEP SEA MINING AND RELATED CHALLENGES

The changing economical and geopolitical climate triggered the exploration for unusual resources, thereby increasing the likelihood that seafloor mineral occurrences become economic reserves. Offshore diamond, phosphate, iron sand, and gold deposits are already being mined on a regular basis using unconventional dredging technologies. In addition to these placer mineral deposits, marine minerals in deep waters are also currently being assessed as future potential resources. Such deposits are located near plate boundaries in ocean basins, which are deemed to be an active source of mineralization in the form of metalliferous sediments, seafloor massive sulphides, manganese nodules, manganese crust, and gas hydrates. Currently, companies involved in deep sea mining are developing state of the art groundbreaking and innovative solutions to mine the ocean floor in a cost effective and efficient way (OceanflOre, 2011).

As technology evolves, deep sea mining is becoming a viable alternative to meet the increasing demand for minerals. Successful operations are built on sound identification of the resource, proper selection of equipment, a thoughtful production plan, and good management. While most effort is put into new technological developments in the field of underwater mining, it is equally vital to understand the management process and risks of constructing and operating an offshore mine. The importance of establishing thorough geotechnical knowledge and understanding of the resource cannot be overstated. During deep sea exploration programs, mineral composition and metal content are often of primary interest because a proper reserve estimation can turn a deposit into a bankable project. On the other hand, for the

development of an underwater mine, a proper geotechnical characterization is also crucial to design and select the proper mining tools which meet the desired functional requirements (Searle & Smit, 2010).

Unfortunately due to the high operating, maintenance, and investment costs of the diving support vessel and the remotely operated vehicle, a sample coverage equivalent to a common land based exploration program would be extremely expensive and highly unlikely. Also the remote location and the technical difficulties to collect samples, further decrease the reliability of the gathered information (van de Ketterij, 2010). This minimal amount of information is interpreted by scientists and engineers and used to build 2D/3D geological models which contain spatial distributions of geotechnical and resource parameters. These spatial parameter distributions are subsequently being used to make decisions regarding equipment design and mine planning.

MODELLING GEOLOGICAL UNCERTAINTY AND ASSESSMENT OF RISK

An efficient Method for Simulation on a Block Scale – a Review of the Local Average Subdivision Method

The Necessity of Geostatistical Simulations

Although, geostatistical estimation theory generally takes off with the ambition to model the probabilistic mechanism of a largely unknown orebody model, the effort eventually results in a way to calculate only the `best' estimate at a single location. The object of such a calculation is to provide, at a specific location (e.g. a mining block), an estimator which is as close as possible to the true unknown grade. The quality of the estimation is measured separately, i.e. independently of neighboring estimates, through its unbiasedness and error variance (Journel & Huijbregts, 1978).

However, a deposit model consisting of an entire collection of such `best' estimates, might not as a whole represent the best model. In general, the minimization of the estimation variance causes a smoothing of the natural variability inherent in the deposit. Yet, this variability has a significant impact on downstream processing steps and fundamentally drives realized value (Benndorf 2013; Benndorf & Dimitrakopoulos, 2010; Goovaerts, 1997; Vann et al., 2012).

As shown in Figure 1, estimation algorithms tend to smooth out local details of the spatial variation of the orebody attribute. Typically, small values are overestimated, whereas large values are underestimated. Another drawback related to this smoothing effect, is that the degree of spatial variation depends on the proximity and density of data locations.

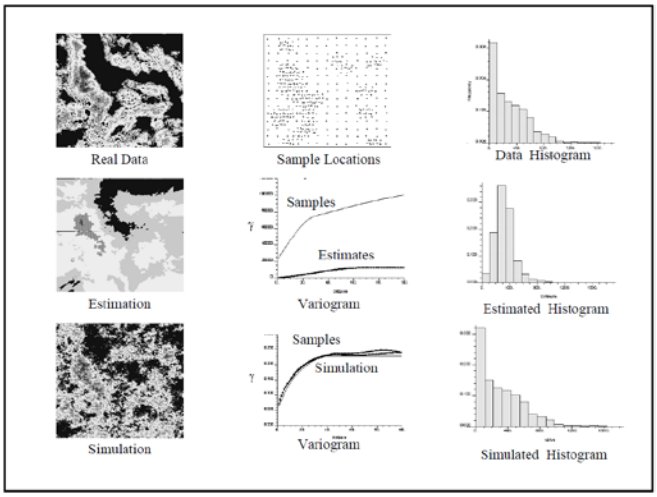


Figure 1 – Estimation versus simulation. Estimation algorithms tend to smooth out local details of spatial variability. The simulation approach, on the other hand, generates a more realistic representation of the in-situ variability (Reproduced after Dimitrakopoulos, 1998).

Probably, the most detrimental consequence of this smoothing effect is the loss of variance, relative to the variance in the initial data. Furthermore, the modeled covariance function is not reproduced by the obtained kriging estimates (Figure 1). The larger the kriging variance on average, the more variance is lost (Webster & Oliver, 2004).

The problems associated with geostatistical estimation are not only caused by its inability to represent the correct spatial variability, but also by the fact that only a single estimated orebody model is generated. Such a single model does not provide the necessary support for risk-based decision making. The use of a single estimated orebody model might lead to incorrect decisions (Dimitrakopoulos, 1998; Martinez, 2009; Savage, 2003).

The cause of this problem can be explained by "Jensen's inequality". In finance, the inequality states that because the value of a project, v, is a random variable and the option value of the project, OV, is a convex function, then $OV(E[v]) \neq E[OV(v)]$. In other words, average input does not always yield average output when dealing with uncertainty and non-linear transfer functions. This flaw of averages further stimulates the use of simulated orebody models.

Local Average Theory and Change of Support

For the generation of simulated ore body models, a large number of possible methods is available. The focus in choosing the right method should be on the application. For industrial scale applications computational efficient methods were developed and successfully applied on a point scale (e.g., Benndorf & Dimitrakopoulos, 2007).

Since decisions are generally made on a block scale, it is convenient to consider a computationally efficient simulation method, which directly generates realizations on a scale of interest related to the smallest mineable unit (SMU). The selected simulation technique essentially consists of two major parts; the simulation phase and the conditioning phase.

First, during the simulation phase, an unconditional random field is generated with a resolution in agreement with the desired SMU scale using a technique called Local Average Subdivision (LAS) (Fenton and Vanmarcke, 1990). The core of this simulation exists out of a sequence of calculation stages, improving the coarse resolution of an initially generated random field. At each calculation stage, the

current image is further discretized by increasing the total number of cells, while reducing their sizes and adjusting their associated values accordingly (Figure 2). The final value of each simulated pixel represents the local average of the modeled ground property. The described focusing operation eventually results in a picture (realization) of the random process, whose statistics are consistent with the desired field resolution.

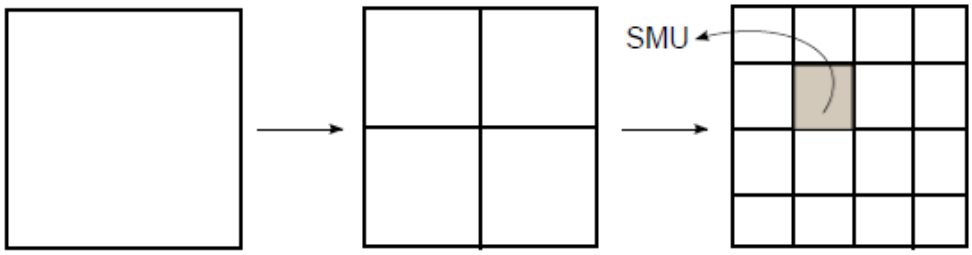


Figure 2 – Resolution improvement during a LAS simulation of a local average random process The coarse resolution of an initially generated random field is improved through a sequence of calculation stages.

Subsequently, during the second phase, a conditioning operation is performed, which ensures that each simulated random field honors the known measurement data.

In mining geostatistics, the simulated or measured material volume with its particular size, shape and orientation is known as the support of the sample. It is important to realize that the sampling size has a considerable influence on the distribution of the obtained values, in particular the variance.

The change of support effect for an arbitrary local averaging operation can be described by a variance reduction formula or computed via a Gaussian Quadrature approximation. A detailed study of the underlying mathematics reveals that local averaging both smooths the process and reduces its variance. The amount of variance reduction turns out to be proportional to the short range variability of the attribute under consideration. The mean of a local average, however, remains constant with a change of support (Fenton & Griffiths, 2008).

The entire benefit of the Local Average Subdivision (LAS) method lies in the fact that this important change of support effect is explicitly modeled. This is in strong contrast with some of the 'conventional' methods, which implicitly model the change of support through a reblocking of point simulations.

Two Dimensional Local Average Subdivision

The acquired understanding of the local average theory can now be used to extend the previously introduced simulation principles (Figure 2) to a proper formulated technique. In two dimensions, the procedure essentially consists of a sequence of calculation stages, during which each cell is further subdivided into four equal sized cells. This subdivision procedure continues until the desired field resolution is obtained.

Figure 3 illustrates a general case, where a certain parent cell, Z_5^i, is further subdivided into four associated child cells $Z_j^{i+1}, j = 1,2,3,4$. Although eventually, the resolution of all the parent cells needs to be improved, only one subdivision is showed in order to retain a certain simplicity.

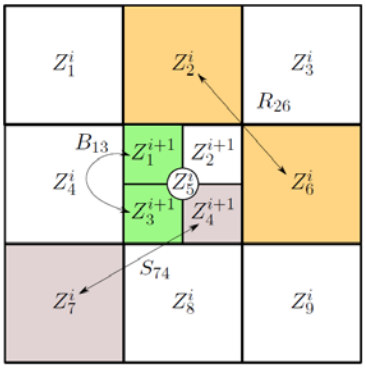


Figure 3 – Cell subdivision in a two dimensional local average subdivision procedure . The procedure consists of a sequence of calculation stages, during which each cell is further subdivided into four equal sized cells. The large squares are the parent cells, whereas the small cells represent the child cells. The connection between the colored squares indicates the three different types of block-to-block covariances that need to be calculated (after Fenton & Vanmarcke, 1990).

Since the single element notation would result in a cluttered collection of equations, the decision was made to use a vector-matrix notation. As such, the four child variables of parent cell, Z_5^i, are stored in one column vector, $\boldsymbol{Z}^{i+1} = \{Z_1^{i+1}, Z_2^{i+1}, Z_3^{i+1}, Z_4^{i+1}\}$, while the nine conditioning parent values are stored in a second column vector, $\boldsymbol{Z}^i = \{Z_1^i, \dots, Z_9^i\}$.

The unknown local averages of the four child cells are subsequently modeled as normally distributed random variables with a mean and variance selected to satisfy the following four criteria:

1. All four local variables average to the parent value, such that the global average remains constant throughout the sequence of subdivisions.
2. All four local variables show a correct variance according to the local average theory.
3. All four local variables are properly correlated with one another.
4. All four local variables are properly correlated with the neighboring child values across the parent boundaries.

The mathematical details of the simulation method can be found in Fenton and Vanmarcke (1990).

Conditioning of the Random Field

In many applications, such as mining, conditioning is important to ensure that the simulated deposit models honor the measurement data at their sampling location (Journel & Huijbregts, 1978). The following formula is used to perform the necessary calculations:

$$Z_c(\boldsymbol{x}) = Z_u(\boldsymbol{x}) + [Z_k(\boldsymbol{x}) - Z_s(\boldsymbol{x})],$$

where $Z_c(\boldsymbol{x})$ represents the conditioned field. The three other components are defined as follows: a) $Z_u(\boldsymbol{x})$ is an unconditional simulation, b) $Z_k(\boldsymbol{x})$ denotes the block kriging estimate based on known measured values at the sampling locations, c) $Z_s(\boldsymbol{x})$ denotes the block kriging estimate based on the unconditional simulated values at the sampling locations.

A New Integrated Framework in a Deep Sea Mining Context for Producing Reliable Results

To increase the applicability of the proposed simulation technique, solutions were developed to overcome some of the most undesirable restraints, e.g., the necessity of normally distributed data and a data support similar to the pixel size of the simulated images.

Moreover, the proposed solution package is integrated in a general simulation procedure that is systematic, robust, and easy to follow. Such a procedure reduces the likelihood of costly mistakes and insures the validity and representativeness of the simulation results (Nowak & Verly, 2004).

The previously described LAS simulation technique constitutes the core of the developed practical process. The other required steps, needed to complete the geostatistical analysis, are ordered and embedded in a visual roadmap (Figure 4). The displayed roadmap indicates that the entire practical process is mainly constructed from three types of components.

1. **The Main Operation** (7): all numbered and located in a vertical sequential path.
2. **The 'Data and Area Statistics' Boxes** (6): all including the same set of tools used to summarize the results of the operations in a few global and spatial statistics.
3. **The Validation Procedures** (2): all designed to control and safeguard the representativeness of the simulation results.

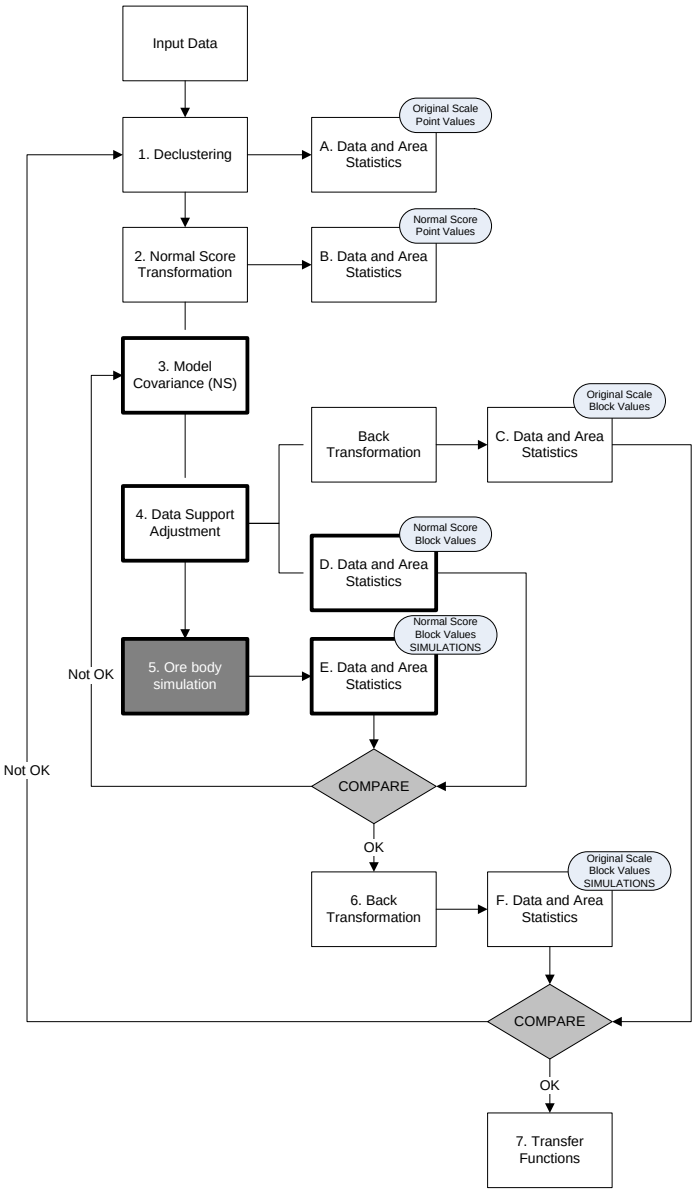


Figure 4 – Roadmap of the developed practical process for the simulation of deep sea deposits.

Data and Area Statistics

The inference process, embedded in each Data and Area Statistics (DAS) box, aims at estimating the same relevant summary statistics for each inserted collection of data values. Each box thus contains the same set of tools to compare the effects and the results of the relevant operations. As the name suggests, the 'Data and Area Statistics' can be subdivided into two categories: a group of global and a group of spatial statistics.

The group of global statistics focuses on the characterization of the general data properties. These general data properties are computed using adjusted formulas for some of the following well known conventional statistical measures: mean, standard deviation, inter quantile range, histogram and cumulative distribution. The conventional formulas are adapted in such a way that they are able to correct the bias due to preferential sampling.

The spatial or area statistics, on the other hand, aim at the estimation of the spatial correlation structures inherently present within the area under investigation. The semi-variance, the covariance and the correlation function belong to the set of tools frequently used to achieve this goal. Also, the calculation of the lag mean, lag variance and some moving window statistics turns out to be particularly useful.

Main Operations

The seven main operations, displayed in Figure 4, constitute the spine of the developed simulation framework. The following list gives a concise overview:

1. *Declustering*; a declustering algorithm has to be performed to remove the bias due to preferential sampling and to make the data more representative for the area under investigation. *Input*: original scale point values; *Output*: original scale point values + declustering weights.
2. *Normal Score Transformation;* the normal distribution constraint on the original data is removed by the application of a normal score transformation.
   Input: original scale point values; *Output*: normal score point values.
3. *Model Covariance Function*: during the third operations, a theoretical model is fitted to the computed experimental covariances of the normal score values.
   Input: normal score point values; *Output*: analytical covariance function.
4. *Data Support Adjustment*: an affine correction overcomes the second constraint, which required that the support of the data was similar to the pixel size of the simulated images.
   Input: normal score point values; *Output*: normal score block values.
5. *Ore Body Simulation*: the combination of random field simulation and conditioning operation results in the generation of equally probable representations of the in-situ ore body variability.
   Input: normal score block values (conditioning data); *Output*: simulated normal score block values.
6. *Back Transformation*: the back transformation is responsible for the representation of the generated ore body models in the original data space.
   Input: simulated normal score block values; *Output*: simulated original scale block values (operation in sequential path). OR
   Input: normal score block values; *Output*; original scale block values (box connected with data support adjustment operation).
7. *Transfer Functions*: economical and technical transfer functions are used to translate the simulated geological and geotechnical models into financial and operational performance indicators.
   Input: original scale simulated block values; *Ouput*: performance indicators. .

Validation Procedures

The goal of the embedded validation procedures is to safeguard the quality and representativeness of the simulation results. Without some kind of validation procedure, even the most sophisticated technique will likely render unreliable results. The proposed practical process contains two main validation steps, displayed in Figure 4 as dark gray diamonds.

1. The first validation procedure is called the inner validation check and is responsible for the quality control within the most internal part of the simulation framework. This internal part, which operates solely in the normal score domain, is indicated by the thick lined boxes (Figure 4). The simulation results are approved if the deviations between the calculated 'Data and Area Statistics' of the simulated normal score block values and those of the conditioning normal score block values stay within acceptable limits.

2. The second validation procedure, encountered in the simulation framework, is called the blanket validation check and is responsible for the approval of the complete set of geostatistical simulation results (Figure 4, lower right). This blanket validation procedure checks if the final

simulation results (after back transformation) reproduce the global and spatial statistics of the conditioning block data.

The practical process was deliberately designed to have this encapsulated double validation procedure. Such an encapsulation makes it easier to detect where in the process the calibration parameters have to be adjusted. A full description of the proposed practical process is given in Wambeke (2013).

QUANTIFYING GEOLOGICAL RISK AT THE OCEAN FLOOR FOR IMPROVED DECISION MAKING

The Concept of the Transfer Function

In order to identify the (financial) project risk or to optimize the design of deep sea extraction equipment, it is necessary to propagate the characterized geological uncertainty through the complete value chain. The obtained spatial distributions thus have to be inserted into physical models, which translate the geological parameters into financial or operational performance indicators. These models, the so-called utility or transfer functions (Dimitrakopoulos, 1998), can be used to calculate for example the cutting force, power requirement, bearing capacity, cash flows, grade tonnage curve, or Net Present Value (NPV).

To further aid the decision making process, the likelihoods and the corresponding (economic) consequences of different scenarios can be compared and evaluated. Often the entire analysis can be summarized, via a decision or forecast model, into a single monetary value which estimates the expected profit, loss or cost associated with each investigated scenario. Typically the scenario that maximizes the monetary value of the mining project is preferred and implemented. This scenario analysis does not necessarily need to be performed explicitly. For certain decision problems, optimization algorithms exists, which automatically explore the different scenarios and produce the 'best' decision.

The main advantage of this briefly described simulation framework lies in the fact that the spatial variability and uncertainty is propagated through the whole equipment design and mine planning process. As such, the whole procedure results in a risk robust decision, adding value to the project. Figure 5 presents a conceptual example of such an analysis.

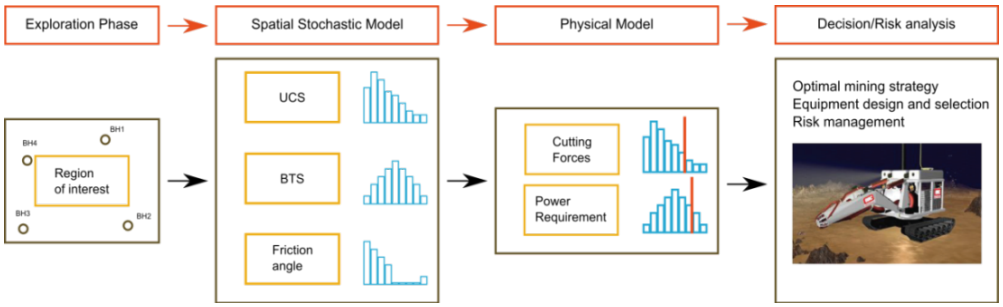


Figure 5 – Conceptual visualization of the added value of the combination between geostatistical simulations and transfer functions. The whole procedure results in a risk robust decision.

Economic Evaluation of a Gold Deposit

The first case study illustrates how the economic value of a gold mining operation can be significantly improved by considering the inherent geological uncertainty during the planning phase. For each excavated block, the production engineer needs to decide whether the mined material can be classified as ore or as waste. Since the economic consequence of misclassification is not symmetric, it definitely pays off to implement a risk-based selection strategy. Decisions thus need to be made based on a comparison between the expected economic consequences of both classification scenarios. The proposed strategy is better capable of exploiting the full potential of each single block.

To illustrate the effectiveness of the risk-based selection strategy, the case study was carried out using an exhaustively sampled, public domain data set (Isaaks & Srivastava, 1989). The data set was modified to represent a horizontal 16m thick rich top layer of a larger deposit on the ocean floor (mean = 2. 9g/ton; median = 2.8 g/ton; std = 2 g/ton; min = 0 g/ton; max = 10.2 g/ton).

This part of the deposit was subsequently subdivided into 288 16x16x16 m^3 blocks. The left hand side of Figure 6 shows one of the 100 obtained realizations with conditionally simulated block concentrations.

In order to keep the case study simple, one can assume that every block in the investigated layer will be mined in a sequential way, starting from the lower left corner, ending in the upper right (Figure 6). Each row of 16 blocks will be completely excavated during a single mining period.

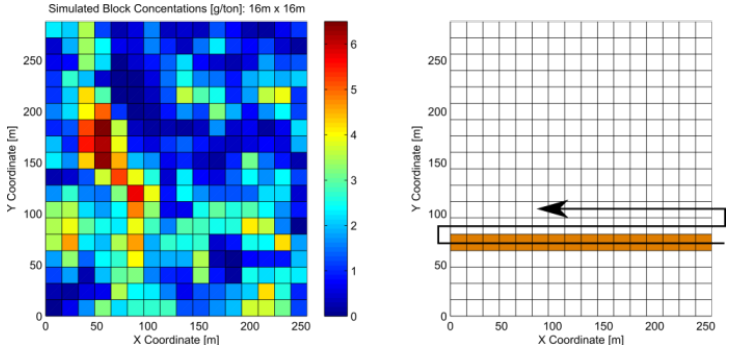


Figure 6 – Preliminary planning of gold mining operation. Simulated gold concentrations in 16x16x16 m^3 blocks (left). Indication of planned extraction sequence. The orange blocks are planned to be excavated during the fifth mining period.

Once a block is excavated, it needs to be classified as either ore or as waste:

- *Scenario 1*: Mined material is regarded as waste and transported to the waste dump at the ocean floor. The costs of this scenario are only limited to excavation and disposal related costs ($\boldsymbol{C_m}$=\$25/ton).
- *Scenario 2:* Mined material is classified as ore, pumped to the surface via a vertical riser, transported with barges to the shore, and treated in the processing plant. This scenario is more expensive and includes mining related ($\boldsymbol{C_m}$=\$25/ton) and a processing related cost ($\boldsymbol{C_p}$=\$75/ton).

A mined block is typically placed in the second logistical loop (scenario 2) if the price of the estimated recovered metal exceeds the sum of the mining, transportation and processing costs. This minimum amount of required metal is generally linked with the economic cut-off grade, which is calculated as:

$$z_{cut-off} = \frac{C_m + C_p}{p.r},$$

where p represents the metal price (\$53/g) and r indicates the percentage of contained metal that can subsequently be recovered (95 %).

Traditionally, the resulting cut-off grade (2g/ton) is compared with a single estimated block grade, in order to classify the mined material (right hand side, Figure 7). However, such a classification strategy does not account for uncertainty and risk. Given the simulated probability distributions, the expected profit associated which each economic scenario of classification can be assessed and used to derive an economically optimal ore selection (Glacken, 1996).

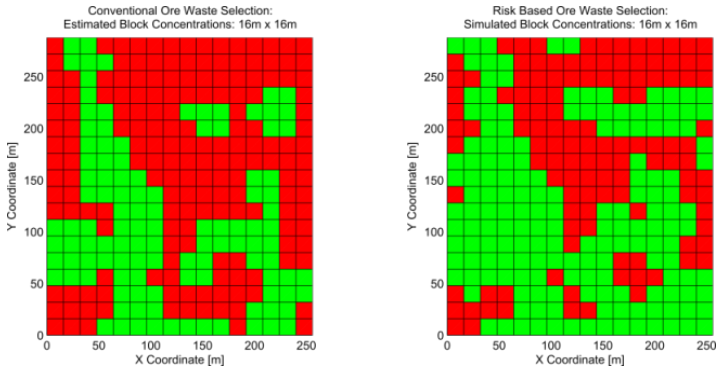


Figure 7 – Improved decision making under the face of geological uncertainty; conventional ore/waste selection based on the estimated block grades (left), risk-based selection based on simulated probability distribution (right). Green = ORE, Red =WASTE.

The expected "profit" of classifying a block as waste is given by:

$$E[Pr_{waste}] = -C_m - P_o.\left[p.r.m^+ - C_p\right],$$

where, P_o is the probability that the true grade of the block exceeds the cut-off grade, m^+ represents the mean grade in the event that the block is classified as ore, and $\left[p.r.m^+ - C_p\right]$ corresponds to the lost opportunity cost. The formula actually indicates that the mining costs need to be paid anyway and that there is a possible loss associated with the disposal of profitable material.

The expected profit of sending a block to the processing plant is:

$$E[Pr_{ore}] = -C_m + P_o.\left[p.r.m^+ - C_p\right] + P_w.\left[p.r.m^- - C_p\right].$$

where P_w is the probability that the true grade of the block is lower than the cut-off grade, m^- represents the mean grade in the event that the block can be regarded as waste, $\left[p.r.m^+ - C_p\right]$ is the possible profit in the case of a correct classification, and $\left[p.r.m^- - C_p\right]$ is a possible additional cost in the case of a misclassification.

Finally, a block is selected as ore if the expected profit for classifying this block as ore is greater than the expected profit of selecting this block as waste. The results of the risk-based selection are illustrated on the right hand side of Figure 7. A comparison between both plots reveals that the risk- based selection strategy results in a slightly greater volume of ore.

The deep sea mining company can subsequently use this plot, in combination with the previously discussed mining sequence, to compute a cash flow analysis. Considering a discount rate of 5 %, the cash flow can eventually be summarized into an NPV.

Figure 8 compares both the predicted and the actual economic consequences of the conventional and risk-based ore/waste selection strategy. The actual economic consequences of both mining plans could have been calculated since the investigated gold deposit is entirely known (Red and Purple bar). The predicted consequence of the conventional ore/waste selection strategy is based on kriged block grades. The predicted consequence of the risk-based ore/waste selection strategy, on the other hand, relies on the collection of simulated realizations. Moreover, the simulation approach yields, besides a most expected NPV, also an indication of the uncertainty on the entire project value. This uncertainty is a direct consequence of the limited amount of available information (470 data points).

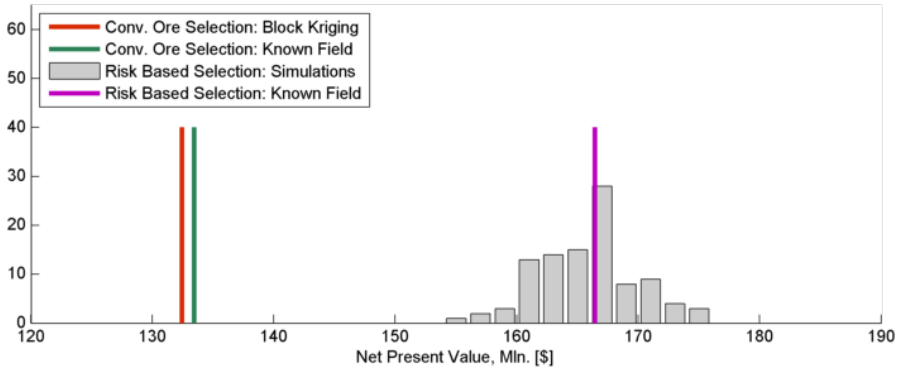


Figure 8 – Net Present Value of the investigated gold mining project. The results from a risk based ore/waste selection strategy are compared with those of a conventional selection strategy.

The case study shows that in this particular case, a risk-based selection strategy can increase the project value by about 25 %. Such a strategy can only be developed when the local geological uncertainty and spatial variability are correctly characterized. Further research needs to be carried out to establish a better understanding of the impact of a change in cut-off grade and other economic parameters on the final decision and the corresponding increase in NPV.

Case Study Equipment Design

The second case study illustrates how a simulation-based geostatistical analysis can be used to support certain decisions regarding equipment selection and design. A collection of technical transfer functions is used to transform the spatial rock strength parameters into equipment requirements. The analysis was performed as follows:

1. A geostatistical simulation is performed to assess and characterize the spatial variability and geological uncertainty in the rock strength parameters (Brazilian Tensile Strength). The tensile strength of the investigated rock varies between 0.5 – 3.2 MPa.
2. The simulated deposit models are subsequently inserted into Evan's cutting formulate to calculate the forces required to excavate the material under investigation (Evans & Pomeroy, 1996). The required cutting forces vary between 0.70 and 4.41 kN.
3. A second transfer function computes based on the previously obtained cutting forces the specific energy, which expresses the amount of energy that is needed to cut one cubic metre of rock. The obtained specific energies vary between 417 and 2635 kJ.
4. Considering a desired production rate of 600 m^3/h, a third and final transfer function can be used to compute the required cutting power. The final calculated values vary between 69.43 and 437.71 kWatt.

Since the collection of technical transfer functions is evaluated over the entire set of simulated realizations, the uncertainty is automatically propagated through the calculations. This means that eventually each cubic metre of material is connected with a specific distribution of required cutting power. The width of each obtained distributions implicitly reflect the inherent uncertainty.

Now, in order to optimize equipment design and to identify areas for additional drilling, a comparison is made between the workability of excavation equipment with an installed power of 200, 300, or 350 kWatt. To facilitate a comparison, the previous simulated block distributions are divided into three categories (Figure 9):

- *Event 1:* The gray cells indicate the regions having a greater than 80 % chance that the required cutting power will be below the limit of the selected mining tool. That is, there is a high probability that the excavation equipment is able to cut the rock.
- *Event 2*: The orange cells indicate the regions having a greater than 80 % chance that the required cutting power will exceeds the limit of the selected mining tool. In these regions, the cutting faces problems during the mining operation. These problems could include lower production rate, high wear, increased maintenance requirements or even breakdown.
- *Event 3*: The purple cells correspond to the intermediate scenario. Due to the local geological uncertainty, it is rather difficult to make reliable statements regarding the cuttability of the rock, with respect to the selected mining tool. The purple cells thus indicate the locations where additional investigations would most likely provide valuable information.

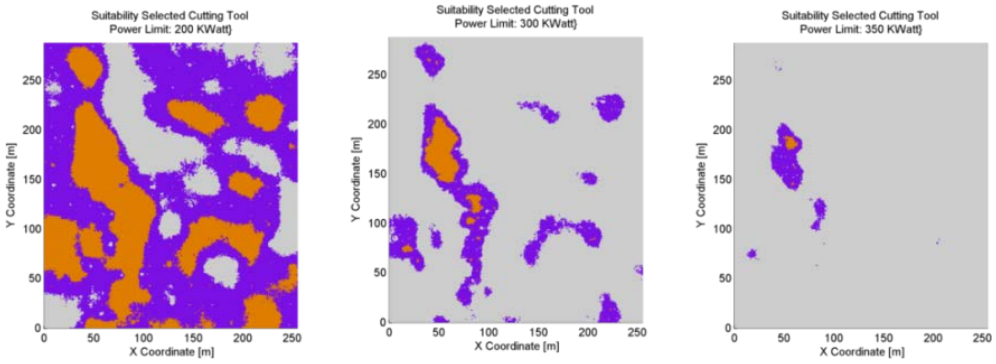


Figure 9 – Decision support regarding installed cutting power. Excavation analysis for 200 kWatt cutting tool (left), 300 kWatt cutting tool (Middle), and 350 kWatt cutting tool (Right).

Some results of the discussed analysis are shown in Figure 9. Only about 25 % of the area can most likely be excavated efficiently with the 200 kWatt excavation equipment. This percentage can be further increased by selecting a more powerful mining tool. Besides a stronger mining tool, the figure also indicates that part of the problem could be solved by a more detailed exploration campaign. Additional information might very well change the classification of areas, now indicated as intermediate, into safe.

To even further optimize equipment design, a detailed risk assessment should be performed, comparing the likelihood and costs of breakdown, wear, and additional maintenance with those of the extra investment costs associated with more powerful equipment.

CONCLUSIONS AND RECOMMENDATIONS

Deep sea mining is becoming a viable alternative to meet the increased demand for minerals. Whilst most effort is put in new technological developments, it is equally important to understand the management processes and risks of constructing and operating an ocean mine. This paper presents the first steps in that direction and mainly focuses on a correct characterization of spatial variability and geological uncertainty.

Due to high operating costs of the diving support vessel and the remotely operated vehicle, a sampling coverage equivalent to a land based exploration program would be extremely expensive and highly unlikely. Due to the high investment costs and the increased risks, it becomes even more important to quantify geological uncertainty and translate it into decision or project risk.

Unfortunately, conventional geostatistical estimation techniques are not capable of correctly characterizing the geological uncertainty. Since estimation models also tend to smooth the spatial variability inherently present in the deposit, they are not suitable to investigate the inherent geological risk. To overcome these restrictions, geostatistical simulation techniques can be used. A correct quantification

and propagation of geological uncertainty results in the sheltering of strategic investments and creates an operation that performs closer to its potential (Dimitrakopoulos et al., 2002). This statement is not only applicable in the context of deep sea operations, but also covers conventional mining.

Since decisions are generally made on a block scale, it is desirable to immediately generate the realizations on the SMU scale of interest. This paper introduces the Local Average Subdivision method (LAS) for generating simulated models of the deposit. The paper introduced a new technique for simulating block concentrations. The proposed simulation method was further integrated into a general framework that is systematic, robust and easy to follow. The accompanying validation guidelines were formulated to reduce the likelihood of costly mistakes and to ensure that the simulation results are representative.

The developed simulation package can subsequently be used to generate an entire collection of correct representations of the spatial variability. The obtained set of realizations is eventually propagated through a selection of transfer functions to translate the geological parameters into financial or technical project risk.

The case studies demonstrated the possible benefit of a probabilistic evaluation approach. Integrating geological uncertainty into decision making substantially increases both the economic performance of classification decisions in mining and the likelihood of optimal equipment design to guarantee a reliable and efficient operation.

The simplified case-studies were only intended to illustrate the potential impact of a risk-based decision strategy in deep sea mining. However, more research needs to be carried out to establish a better understanding of the selectivity of seafloor excavation equipment and its impact on the final mine design. The ore/waste decision possibly needs to be made on slurry volumes instead of on the conventional mining block.

The economic model of the discussed deep sea mining operation still needs a lot of improvement and should actually consider three cost components; excavation costs, transportation costs and processing costs. A single excavation cost for ore and waste can be considered. The transportation costs however might differ substantially. Waste needs to be pumped horizontally, possibly over a large distance, on the ocean floor to a disposal area (question still remains if such permission would be granted). Ore, on the other hand, needs to be pumped horizontally to the vertical riser assembly, then lifted to the surface, transported with barges to the shore and finally transported to the processing plant. Processing costs need to be taken into account for ore only.

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