EMBRACING GEOLOGICAL UNCERTAINTY IN MARINE RESOURCE EXPLORATION AND EXPLOITATION

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As land resources decrease and technology evolves, deep sea mining is becoming a viable alternative to meet increasing demand for minerals. In order to run an optimal operation, the impact of the spatial variability and geological uncertainty on the equipment selection and production plan need to be understood. To address this problem, a risk quantification framework has been developed which makes use of state of the art geostatistical simulation methods to generate different possible geological scenarios. The resulting scenarios are subsequently inserted into so-called transfer functions which translate the geological parameters into financial or operational key performance indicators. Case studies illustrate the benefits of a risk based approach during a cash flow analysis and an equipment selection.

The necessity of geostatistical simulations

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 in the context of deep sea mining. Also the remote location and the technical difficulties to collect samples, further decrease the reliability of the gathered information. This minimal amount of information is interpreted by scientists and engineers and used to build 2D/3D geological models that 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.

Although the geostatistical estimation theory generally starts 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 that 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 thus also on the final realized value (Goovaerts, 1997; Benndorf & Dimitrakopoulos, 2010).

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).

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 \( E[OV(v)] \neq E[OV(E[v])] \). 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.
Since decisions are generally made on a block scale, a new computationally efficient simulation methodology was developed, which directly generates several plausible realizations on a scale of interest related to the smallest minable unit (SMU). The core of the simulation technique 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 (Wambeke, 2013).

Quantifying geological risk at the ocean floor for improved decision making

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).

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 1 m thick rich top layer of a larger deposit on the ocean floor (mean = 2.9 g/t; median = 2.8 g/t; standard deviation = 2 g/t; min = 0 g/t; max = 10.2 g/t). The average density of the material is 2.7 t/m$^3$.

This part of the deposit was subsequently subdivided into 288 $16 \times 16$ m$^2$ blocks with a unit thickness. The left hand side of Figure 1 shows one of the 100 obtained realizations with conditionally simulated block concentrations.

![Figure 1. Preliminary planning of gold mining operation. Simulated gold concentrations in 16 ×16 m$^2$ blocks with a unit thickness (left). Indication of planned extraction sequence. The grey blocks are planned to be excavated during the fifth mining period (right).](image-url)
In order to keep the case study simple, one can assume that every block in the investigated layer will be excavated in a sequential way, starting from the lower left corner, ending in the upper right (Figure 1). Each of the 18 rows contain 16 blocks will be completely excavated during a single 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 related to this scenario include excavation costs (15$/t) and horizontal transportation and disposal costs (10$/t).

- **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 excavation costs (15$/tonne), transportation costs (30$/tonne) and processing related costs (55$/tonne).

A mined block typically moves through the second logistical scenario, 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:

\[
z_{\text{cut-off}} = \frac{15+30+55}{p.r}
\]

where \(p\) represents the metal price (553/g) and \(r\) indicates the percentage of contained metal that can subsequently be recovered (95%).

Figure 2. Improved decision making under the face of geological uncertainty for conventional ore/waste selection based on the estimated block grades (left) and risk-based selection based on simulated probability distribution (right). grey = ore, white = waste.

Traditionally, the resulting cut-off grade (2 g/t) is compared with a single estimated block grade, in order to classify the mined material (Figure 2, left). 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). The expected “profit” of classifying a block as waste is given by:

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

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 \(p.r. m^+ - C_p\) 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:

\[ E[P_{\text{ore}}] = -C_m + P_m \left[ p \cdot r \cdot m^+ - C_p \right] + P_w \left[ p \cdot r \cdot m^- - C_p \right] \]  

where \( P_m \) 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, \( [p \cdot r \cdot m^+ - C_p] \) is the possible profit in the case of a correct classification, and \( [p \cdot r \cdot m^- - C_p] \) 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 in Figure 2. 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 3 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 bars in Figure 3).

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, besides a most expected NPV the simulation approach yields an indication of the uncertainty on the entire project value. This uncertainty is a direct consequence of the limited amount of available information.

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. A total of 73,728 one
square metre blocks with a unit thickness were simulated in an area of $288 \times 256$ m$^2$. The analysis is 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 and 3.2 MPa.
2. The simulated deposit models are subsequently inserted into Evan’s cutting formulation 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 m$^3$ of rock. The obtained specific energies vary between 417 and 2,635 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 kW.

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 kW. To facilitate a comparison, the previous simulated block distributions are divided into three categories (Figure 6).

- **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 exceed 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.

Some results of the discussed analysis are shown in Figure 4. Only about 25 % of the area can most likely be excavated efficiently with the 200 kWatt excavation equipment (Figure 4, left). This percentage can be further increased by selecting a more powerful mining tool (Figure 4, middle-right). 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

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, Farelly, & Godoy, 2002). This statement is not only applicable in the context of conventional mining, but also applies to deep sea operations.

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 demonstrate 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.

REFERENCES


