RECENT DEVELOPMENTS IN GEOSTATISTICAL RESOURCE EVALUATION - LEARNING FROM PRODUCTION DATA FOR OPTIMIZED EXTRACTION OF MINERAL RESOURCES

J. Benndorf, Delft University of Technology, NL

Abstract

The resource model is the foundation for mineral project evaluation, mine planning and operations production control. The representativeness of such a model depends on both, the quality of data available and the modelling technique applied. This contribution reviews recent developments in geostatistical resource modelling first focusing on mapping uncertainty and evaluation project risk. In this context a method is briefly described, which allows the inference of geostatistical model parameters in the presence of strong trends. The second part introduces a concept for integrating online production data for updating resource/reserve models. The ability to utilize the value of this additional information and feed it back into reserve block models and planning assumptions leads to a Real-Time Mining concept and opens up new opportunities to continuously improve decisions made in production planning aiming for increased resource recovery and process efficiency.

Requirements for a resource efficient exploitation

To secure the raw materials supply of the current and future generations, the exploitation of mineral resources moves towards deposits, which are geologically more complex and variable, lower in grade or more difficult to access. Further, due to difficult access, information about the extent and geometry and also the spatial distribution of relevant attributes within the deposit are limited. Recent examples of these developments include the trend to mega block cave mining technology for mass – mining underground extraction [e.g. 1] or Europe’s initiative to make deep sea resources accessible [e.g. 2]. Sustainable exploitation requires ensuring a safe operation, limiting the impact to society and environment to an acceptable level and justifying large up-front investments and operational costs. In addition, to maintain options for future generation, the exploitation effort needs to aim for the maximal utilization of the mineral resource in place.

Understanding the risk originating from the limited information about the orebody plays a key role in deciding on project options and investments and also to perform optimal mine planning and operational control. Examples show that limited information and insufficient resource modelling effort has led to unfavorable decisions, unexpected additional expenses and costs, unsafe conditions and as well to underperformance of the mining operation [3,4].

Developments in mineral resource modelling over the past two decades focused on developing methods that allow understanding the geological risk linked to decision making. Techniques of conditional simulation in geostatistics are nowadays routinely applied for mapping geological uncertainty and risk associated with not meeting production targets or financial and environmental indicators [e.g. 5,6]. More recent developments focus specific challenges such as geo-metallurgical modeling for improved processing and refining operations or to handle strong trends in the data [7, 8, 9]. These methods are mainly
based on data gathered during the exploration phase. The information processing through the mining-value-chain from exploration through resource/reserve estimation, mine planning, operations management and processing generally occurs discontinuously over long time spans. Reacting to deviations between produced ore and model based expectations, reconciliation exercises are performed adjusting resource models and mine planning assumptions. However, here is often a lag of weeks, months or even years.

Developments over the last decade have created a flood of online data about different aspects during the production process. For example, sensor technology enables online characterization of geochemical, mineralogical and physical material characteristics on conveyor belts. As well equipment performance data, such as the mill energy usage include valuable information on characteristics of the fed material. The ability to fully exploit this additional information and rapidly feed it back into resource models will open up new opportunities for improved decision making in short-term planning and operational control. The certainty in predicting local grades for mining blocks is expected to increase leading to a decrease in frequency of misclassification and unfavorable dispatch decisions. As a result quality control of the produced raw material will improve significantly. Buxton and Benndorf [10] quantified this value along the complete value chain in the order of multiple tens of millions of USD per annum in an average sized operation. Recently a formal framework was introduced for rapid resource model updating based on online available production data [11].

This contribution reviews recent developments in geostatistical resource evaluation for improved decision making. First, concepts of conditional simulation applied to mine planning will be illustrated. Second, a technique for dealing with strong trends in the data is outlined. The last section introduced the intuitive concept of rapid resource model updating based on online production data utilizing a closed-loop concept.

Understanding the impact of uncertainty in resource estimation

A framework for quantifying geological risk integrates two main elements:

(1) modelling geological uncertainty and
(2) evaluating project risk due to geological uncertainty.

Following subsections provide a brief introduction to each of the elements. For more detailed information the given references provide a good start for the interested reader.

Modelling geological uncertainty

The majority of decisions in mining, such as equipment selection and specification, the optimization of a short- or long term mine plan or the design of blending opportunities are based on the understanding about the orebody captured in one estimated ore body model. Although estimated models can be quiet good locally, they also exhibit a smoothing effect. To account for variability and grade uncertainty, methods of conditional simulation have been increasingly applied in geostatistical modelling over the last two decades [e.g. 12]. Conditional simulation is a Monte-Carlo-Simulation based technique that allows generating multiple possible models or scenarios of the deposit based on the information available, e.g. exploration drill holes. Each model is called realization and reproduces available data and information, statistics and spatial variability. In the terms of geostatistics, the generated models reproduce the representative data histogram and the variogram. Figure
1 shows a comparison between models generated by interpolation and simulation for a multi-seam coal deposit. A visual inspection of the models illustrates the differences very well. The interpolated model suggests a very smooth seam geometry and distribution of calorific value, however, this smoothness does not represent what was found in the data. Essentially this smooth behavior does not represent reality. The two simulated models exhibit features inferred from data, namely the variability. Each realization captures the global structure of the deposit but exhibits a different behavior at a local scale.

Figure 1: Comparison between deposit models based on interpolation and simulation in geostatistics [after 13]

Analyzing the spread of values from different realizations at a location, say a mining block, allows for quantifying uncertainty in prediction and inferring probabilities of exceeding certain thresholds.

Applications of conditional simulation in mining present their own challenges, including the size of simulations, computational efficiency and data management. Large ore body models, frequently discretized by up to millions grid nodes, need to be generated. The development of algorithms for mining application has to take this requirement into account.

Generally, techniques can be divided into direct conditional simulation methods and two-step methods. Two-step methods, such as the almost historical turning bands [14] or spectral methods [15, 16] first generate unconditional simulations, which are conditioned to the data by Kriging afterwards. This involves redundant computations and increases computational costs. Direct conditional simulation methods, such as sequential methods [17, 18] and conditional simulation via covariance matrix decomposition [19] perform the conditioning step during the simulation process. Dimitrakopoulos and Luo [20] suggest the theoretical background for a computationally efficient method, the Generalized Sequential
Gaussian Simulation (GSGS). This sequential simulation approach simulates groups of clustered nodes simultaneously instead node-by-node, which decreases computing time. Benndorf and Dimitrakopoulos [21] investigated practical aspects of GSGS and demonstrated its benefits in terms of runtime in a case study. Applied to a copper ore body of 14.000.000 grid nodes GSGS run 20 times faster than a similar implementation of the traditional Sequential Gaussian Simulation. Most recent development focuses on the simulation of complex ore geometries, as for example found in Kimberlite pipes. Suitable simulation methods use high order statistics instead of variogram based two-point statistics [22] or make use of training images such as multi-point statistics [e.g. 23].

Evaluating geological project risk

The concept of quantifying risk due to geological uncertainty is based on a general framework of ore body uncertainty in mining projects [24, 25]. Based on several equally possible ore body models, the mining process or sequence of processes, such as open pit design or production scheduling, is conceptualized as transfer function. For a set of simulated ore body models the transfer function will generate a distribution of the response, which defines its space of uncertainty. Response values are usually key performance indicators of the project such as the net present value (NPV), tonnage or grades. Figure 2 illustrates the concept. It is important to recognize that in general the transfer function is a non-linear function. The consequence is that an average type ore body model, such as generated from an interpolation algorithm, may not provide the average of response uncertainty. This often generates a bias leading to non-optimal decisions.

An example of a simulation based risk assessment in mining was performed for a coal deposit [13]. For a given deposit with a defined level of exploration a mine plan was evaluated with respect to its economic performance (Figure 3). Based on estimated CAPEX and OPEX figures and the long-term mining sequence the interpolated model resulted in a single NPV-forecast of 42,7 Mio. Euro. Applying 25 simulated deposit models to the evaluation procedure, a distribution of possible NPV’s was generated as shown in Figure 3. When analyzing this distribution, it is somewhat surprising that the interpolation based forecast will never be achieved. In the best case, executing the mine plan will generate an NPV of 39,8 Mio Euro, in the worst case only 27,2 Mio Euro. The expected value of the risk based approach is about 36,2 Mio Euro and is significant less than the interpolation based estimation. The reason for this phenomenon is the non-linear transfer function “Mine Plan”. Variability, which is not captured in the interpolated model, causes deviations from production targets leading eventually to a negative economic impact. It is important to state at this point that the here quantified uncertainty is solely due to geological uncertainty and does not take into account other factors, such as uncertainty in market price.
The spread between Minimum and Maximum of 9.0 Mio Euro is of additional interest. This amount is an expression of imperfect knowledge about the deposit. The ability to quantify the “costs of imperfect knowledge” provides the means for improving decisions in exploration. The left side of Figure 3 displays a typical diagram for optimizing exploration expenditure. It shows the exploration costs as function of spacing between drill holes $K(s)$ and the expected earnings as function of the spacing $G(s)$. Intuitively, the exploration costs decrease with drill-hole spacing as do the earnings, because increasing geological uncertainty increase the frequency and magnitude of deviations from production targets. Utilizing the information from simulation based evaluation, $G(s)$ can be quantified before
the operation is commissioning and strategic decisions regarding exploration expenditures is made. Linking directly the economic consequence with the level of exploration is an essential part in reporting resources and reserves according international standards, e.g. the Australian JORC –Code [26].

Geostatistical modelling in the presence of strong trends

Despite the improvements made in the field of orebody simulations, it remains challenging to model attributes with non-stationary first order moments. Often regional or global trends are present in orebody attributes and have to be taken into account while modelling. In particular the definition of geostatistical model parameters captured in the variogram is difficult since the experimental variogram is overprinted by effects of the trend. Traditionally, semi-stationary residuals are obtained either by delineation of domains or by explicit modelling of a trend. A variety of trend modelling approaches exists. Data in geological sections can be manually or automatically contoured; trend surface analysis, a form of multiple regression, fits polynomials by least squares to the spatial coordinates; in densely sampled areas, moving window averages can be calculated.

In practice, it is usually not possible to unambiguously identify and separate the smoothly varying trend from the more erratic residuals. However, the inference of the trend model is critical due to its influence on the residuals. A misfit could result in a severe bias during the assessment of uncertainty [27].

Recently, a new approach to infer covariance model parameters without the need of the prior trend removal was introduced [28]. It is designed to optimally split trend and residuals components based on Dual Kriging. The method uses average empirical and theoretical differences between two methods of prediction, which are compared and have to be matched.

“If the model parameters, which are used for the calculation of both measures of errors in prediction, are neither fitting the data measured nor the structural behaviour of the attribute under consideration, a discrepancy between the theoretical and empirical error will occur.”

The comparison of errors is performed for groups of distances between the point to estimate and data (ring of influences). By analyzing the error curves for different rings of influence, the fit of the complete covariance model can be assessed. The nature of the mismatch between both error curves provides an indication on how the model parameters need to be adjusted. (Figure 4). Vertical differences can be adjusted using the sill or nugget-effect parameter. Horizontal differences can be adjusted using the range of the variogram. For a more detailed description of practical aspects of the method the reader is referred to Wambeke and Benndorf [9].
Wambeke and Benndorf [9] applied this approach in a large field study in a heavy minerals sand deposit and demonstrate the applicability and validity of the methodology. Results demonstrate the added value and strength of the error-curve based simulation approach. It is capable of reproducing complex features described by the field geologists. Figure 5 shows the reproduction of strong horizontal trends of the slime content. A validation study indicated that all simulation objective were met, i.e. the uncertainty and spatial variability was correctly characterized.

**Figure 4:** Assessment of theoretical and empirical error curves: model parameters are not carefully chosen (left) and a good model fit (right)

**Figure 5:** Simulated Realization of a heavy mineral deposit with strong horizontal trends (after [9])

**Integrating online-production data for improved decision making**

Previously described methods allow the quantification of uncertainty. Although sophisticated, no different or additional information are used. In fact, the actual precision of the model does not increase, it is just quantified. The ability to utilize all available online
production data for a real-time feed-back and continuously optimization has the potential to further improve resource models and decrease prediction errors. An innovative real time model -reconciliation and optimization of the production process was recently developed in petroleum reservoir management [29] and demonstrated increased process efficiency in the order of 6% to 9%.

The following sections introduce a framework for real-time feedback of sensor derived online data into the resource model. The framework consists of three parts (1) a model based forecast at the sensor station, (2) a sensor measurement and (3) posterior updating of the resource model based on differences between model based prediction and sensor data. The latter one is a challenging task. The material stream passing a sensor station may be composed from different sub-streams coming from different excavators working at different parts in the deposit. Figure 6 illustrates this case for a continuous open pit and an underground mine. The raw material is mined on multiple benches or from different mining faces. The flow of material is combined leading to the coal stock- and blending yard or a central bunker. If the sensors are located above the central conveyor the determination it is difficult to track back the differences between model based prediction and sensor measurement as the raw material stream comes from different sources which different prediction accuracies in the resource models. In this respect the accuracy of the sensor has to be taken into account as well.

![Diagram](image)

**Figure 6:** Closed-loop concept in a continuous mining operation

To account for different data originating from different sources with a different data quality, density and support, the currently used methods in geostatistical modelling and data fusion have to be extended. Different data, e.g. from exploration holes and lab analysis, online responses of sensors, GPS measurements of actually mined raw material or geodetic survey data have to be integrated consistently to update the reserve model in a Bayesian fashion. In addition, the material characterised at sensor locations may represent a blend of material originating from multiple extraction phases. In order to feed back the sensor information the influence of material originating from each extraction face has to be separated.

To solve these challenges of multiple solutions are possible. Benndorf [11] proposes a modification of Kalman-Filter techniques, which are designed to sequentially estimate the system states, in this case the local grades at excavation locations, recursively on the basis of noisy input data measured. Kalman [30] introduced a method in the context of system and control theory describing a recursive solution to estimate the state of a
stochastic process $Z^{t+1}$ at time $t+1$ based on a prior model of the state $Z^t$ at time $t$ and observations $l$ at time $t$.

To update a spatial resource model, the system state is put in a spatial content and represents the block model estimate $Z(x)$, and the observations correspond to sensor measurements during a production period of a certain time span, e.g. 5 minutes or 1 hour.

The idea is to update the resource model, denoted with $Z^{t+1}(x)$ as a linear combination of the prior block model $Z_t(x)$ and the difference between model based prediction and the vector of sensor based measurements $l$ (Equation 1).

$$Z^{t+1}(x) = Z^t(x) + K(l - AZ^t(x))$$  \hspace{1cm} (1)

Matrix $A$ is a design matrix and captures the contribution of each reserve block per time interval to the raw material flow produced and observed at a sensor station. The term $AZ^t(x)$ represents the model-based prediction and integrates the operative decisions (digging capacity and location of excavators at each time) in $A$ and the prior resource/reserve model $Z_t(x)$. The objective is to determine the matrix $K$, which is the unknown updating factor (Kalman-Gain) as a best linear and unbiased estimator. A detailed derivation is not scope of this paper and the reader is referred [11]. It can be shown that

$$K = (A^T C_{zz} A + C_{ll})^{-1} A^T C_{zz}$$  \hspace{1cm} (2)

An interpretation of equation (2) reveals the integrative character of the Kalman-Gain. The first term is the inverse of two error sources: (a) the model prediction error, represented by the covariance matrix of the prior resource model $C_{zz}$, which is propagated through the mining system by the design matrix $A$ and the prior resource/reserve model $Z_t(x)$. The second term represents again the error source of the model-based prediction. A comparison of potential magnitudes of the two error terms reveals that:

- if the model error is large and the measurement error small, the Kalman-gain $K$ tends towards 1. The application to equation (1) shows that the full difference between model-based prediction and sensor-based measurement is taken into account to update the resource/reserve model.
- if the model error is small and the measurement error large, the Kalman-gain $K$ tends towards 0. The application to equation (1) indicates that the difference between model-based prediction and sensor-based measurement is not taken into account to update the resource/reserve model. The precision of the sensor is too low to add value to estimation of resources and reserves.

It is intuitive that with the integration of sensor-data in the resource/reserve model the prediction uncertainty is decreasing. This is not only the case for reserve blocks, which are currently excavated but as well for adjacent blocks to be excavated, because these are spatially correlated. It can be shown that the improvement in model prediction can be quantified by

$$C_{zz}^{t+1} = C_{zz}^t - K A C_{zz}^t$$  \hspace{1cm} (3)

where $C_{zz}^{t+1}$ is the updated posterior model covariance matrix, which is by definition smaller than the prior model covariance matrix $C_{zz}$. The updating concept is summarized in Figure 7.
The so far presented method is limited to normally distributed errors and linear relationships in the design matrix $A$. These assumptions are not always valid in mineral resource extraction, as grades may not be distributed normally and reserve estimation include non-linear elements, such as cut-off grades, losses and dilutions. Expression (3) would not be valid. The so called Ensemble Kalman-Filter [31] offers a solution, which is founded upon the Monte-Carlo concept (Figure 8). Based on an ensemble of possible scenarios of the resource model, which capture the uncertainty and variability in estimation, the application of equation (1) to each of the ensemble members leads to updated scenarios. A statistical evaluation of the updated models leads to an empirical representation of the new model error $C_{zz}^{\text{ERR}}$. The Ensemble members can be generated using commonly applied techniques of conditional simulation in geostatistics [e.g. 12].
An illustrative case study

The subsequent example aims to investigate the performance of the proposed updating methodology for different mining system configurations and sensor precisions. For deeper insights in the continuous mine system simulation for short-term planning and decision control under geological uncertainty, the reader is referred to [32]. Here an artificial test case presented, which is built around the well-known and fully understood Walker Lake data set [33]. The data set (Figure 9) is interpreted as quality parameter of a coal deposit, e.g. as calorific value. It is sampled irregularly at a spacing corresponding to an average of two reserve block length. The blocks were defined with a dimension of 16m x 16m x 10m. The block -variogram is given with a spherical structure, range 50m, nugget effect 0.4 and sill 0.6.

Taking into account an assumed density of 2 t/m3 one mining block represents a tonnage of 5.120 t. Ordinary Kriging was used to generate a resource block model and the prior error covariance matrix, Generalized Sequential Gaussian Simulation was used to derive the realizations or ensemble members for the EnKF application. For simplicity, no dilution and losses were applied resulting in the reserve model being equal to the resource model. The resulting block model (Figure 9) was used as prior model.

Without loss of generality the artificial block model shall be mined applying a continuous mining system, which contains initially of two bucket-wheel excavators positioned at separate benches. Figure 9 shows the extraction sequence for the case of two excavators. Different digging rates were applied: Excavator one mines at a rate of 500t/h and excavator two at 1.000t/h. The material is discharged on belt-conveyors positioned on the benches, which are combined to one material flow at the central mass distribution point. The belt speed is assumed to be constant at 6m/s.

The combined material flow of both excavators is scanned by a sensor positioned above a central conveyor feeding the stock- and blending yard. Since no real sensor data are available, virtual sensor data were generated. The artificial sensor data represent a 10 minute moving average (corresponding to about 250 t production) and are composed of three components. Component one is the true block grade taken from the exhaustively known data set. Component two captures the volume variance relationship and corrects the smaller sensor-measurement support of 250t to the mining block support of 5120t by adding the corresponding dispersion variance. The third component mimics the precision
of the sensor. For this case study the relative sensor error is varied between 1%, 5% and 10%.

The performance of the proposed Kalman-Filter approach will be evaluated using two measures. The first measure is the mean square difference or mean square error (MSE) related to the true block value. Here, the difference between estimated block value $z^{t+1}(x)$ and real block value $z(x)$ from the exhaustive data set is compared. The MSE is an empirical error measure and can be calculated according to

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (z^{t+1}(x_i) - z(x_i))^2 \quad (4)$$

Figure 10 shows the MSE for different sensor precisions compared to the prior case for blocks,

- which are already mined,
- which are one block distant and will be mined next working shift, day or week and
- which are two blocks distant and will be mined in near future.

The upper row shows results from the Kalman Filter, the lower row shows results obtained by the Ensemble Kalman Filter.

![Figure 10: Evaluation of results for resource model updating using the Kalman-Filter (KF) and the Ensemble Kalman-Filter (EnKF)](image)

Figure 10 demonstrates clearly the ability of the presented Kalman-Filter based approach to decrease the uncertainty of predicting block values by updating based on sensor data. Considering the MSE, following observations can be made:

For mined blocks, the uncertainty almost vanishes. This is expected because in case of one excavator the sensor measurements can be unambiguously tracked back to the source block. Residual uncertainties remain due to the sensor precision.

Adjacent blocks are updated resulting in a significant improvement compared to the prior model. For high precision sensors this improvement leads to an about 40% decrease of the MSE. This improvement is due to the positive covariance between two adjacent blocks. In addition, the sensor clearly influences the result.
Blocks in the second next row are still updated. Due to the larger distance and the corresponding smaller covariance, the effect is less obvious compared to directly adjacent blocks, however, still significant.

The differences in block model are shown in Figure 11. It shows the prior model based on exploration data, the newly updated model and the differences between both models. Clearly the model is updated.

With this framework an efficient method is available to integrate production data with exploration data for a continuous updating of the resource model.

![Figure 11: Comparison between block models: prior model, updated model and difference](image)

**Future outlook – Real-time mining**

Developments in geostatistical resource modelling over the past two decades have enabled the mining engineer to understand the uncertainty in the resource/reserve estimation and understand the corresponding project risk. In this contribution selected examples illustrated the practicality and the value generated, when using modern techniques of conditional simulation in geostatistics.
The ability to incorporate online sensor data, derived during the production process, into resource/reserve models promises a large potential for improvement in efficiency in any type of mining operation. With the variety of Kalman-Filter based techniques a set of tools is available, which lead to an improved prediction of critical attributes in the resource/reserve model.

The updated model will lead to possibly new decisions in short-term operation management such as production sequencing, digging capacity control or stock-pile management. Mine Process simulation approaches offer a solution to quickly evaluate and optimize alternative decisions for improved decision making. Simulation based optimization methods (Figure 12), such as Response Surface Methods or Learning Automata Search, have been proven to result in near optimal solutions for decision problems and are especially applicable for scheduling complex and computationally large systems [34,32] such as continuous mining operations.

![Figure 12: Concept of simulation based optimization](image)

Having available powerful simulation tools for mining systems, such as the impact of a set of short-term or control decision variables can be evaluated. Simulation based optimization is based on an iterative perturbation of decision variables and the mapping of the corresponding objective value J. Utilizing the Response Surface Method the objective value can be mapped as a function of decision variables, even if not all possible combinations are tested. The efficient exploration of combinations of decision variables can be supported by stochastic gradient descent methods.

Integrating resource model updating, simulation and simulation based optimization leads to a near-continuous process monitoring and production control framework. With an implemented framework further questions can be answered, such as: “What is an efficient monitoring network for the system?” or “What implications does the knowledge gained have on the long-term planning and necessary level of exploration?” In particular the last question is interesting as it investigates the utilization of additional sensor data for mine planning and suggests that the level of “traditional” exploration may be decreased in future. New exploration strategies for a “self-learning-mine” have to be developed that incorporate the time-effect of available information and maximize the use of it.

In the Resource Engineering Section at the University of Technology in Delft, the Netherlands, current research projects are underway to mature this framework.
References


