Dr. – Ing. MPhil Jörg Benndorf
Assistant Professor Resource-Engineering
TU Delft |
Department of Geosciences & Engineering |
Faculty of CEG |
Delft | Netherlands

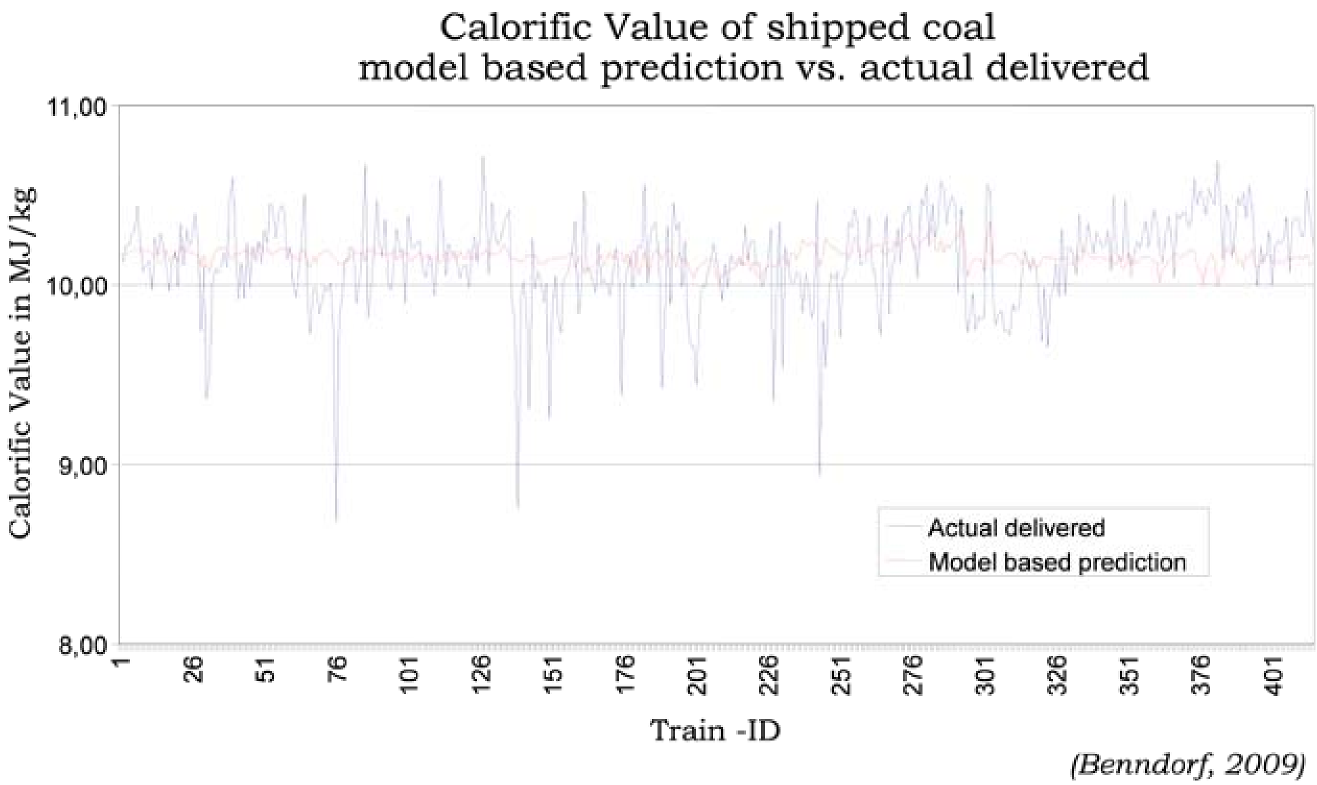
# Adding project value by managing geological risk in mining

## Geological uncertainty and its effects on financial project performance

The mining industry as a business is quite distinct to other manufacturing ventures. It is characterised by a value chain, which elementary production factor is not completely known or fully understood - the mineral deposit. Information about the deposit in terms of spatial grade distribution is scarce and taken from only few drill-holes compared to the whole extension of the deposit. A gross figure for the relation between volume sampled and volume of the entire ore body in the mining industry is given by Dagbert (2003) with 1: 10.000.000. In other words, one kg of sample represents 10.000t of ore to be mined or five to ten train loads. It is obvious that there is some uncertainty associated with estimating the local grades and eventually the grades of a train load. This uncertainty has a strong impact on the economic performance of any project. Most mining projects sell "products" of ore defined in tight quality bands to costumers. In iron ore, train or ship loads have to be delivered in a certain range between upper and lower quality limits for multiple elements including Al2O3, SiO2, P or LOI (Stone et al, 2004). Another example is coal, which has to be shipped in certain limits to the power plants to guarantee an efficient and environmental responsible energy production.

Figure 1 shows a typical compassion between model based prediction and actual shipped calorific value of delivered coal. Certainly the actual variability is significantly larger than the prediction suggested. Deviations from production targets cause inefficiencies in subsequent processes, penalties and directly impact the cash flow of the overall project. To understand the interaction between mineral resource, mining equipment, mining process and product quality and for best decision making, geological uncertainty needs to be well understood. ▶

*Fig. 1:*
*Model based prediction vs. actual delivered calorific value (Benndorf, 2009).*



Questions like:

- *"What is the current knowledge about the ore body?",*
- *"What is a desired level of confidence of knowledge to make best decisions?",*
- *"Which exploration effort is required to obtain the desired level of confidence?" or*
- *"Which frequency and magnitude of deviations are to be expected, when executing a certain mine plan?"*

are essential to ask to understand and manage geological project risk.

Traditional methods in mine planning and production management are based on single interpolated ore body model, using for example Kriging. Although these models can be quiet good locally, they also exhibit a smoothing effect. Typically, low-grade values are overestimated whereas high-grade values are underestimated (David, 1977; David, 1988). Interpolation methods are unable to account for in-situ variability and uncertainty associated with the description of the ore body.

The ability to model geological uncertainty, utilising it for quantifying project risk and its integration into long- and short-term production scheduling opens up a high potential to decreases project risk and enhances project profitability.

One direction of future research in Resource Engineering at TU Delft will involve the development of a framework for managing geological risk and the application to different stages in a mining project. The following contribution will provide an overview of a framework of risk based decision making in mining. It integrates methods of modelling geological uncertainty by the means of conditional simulation in geostatistics, the concept of a transfer function to quantify project risk and to optimisation algorithms for mine planning. Selected examples along the mine value chain will illustrate the concepts and demonstrate the significant benefit of the risk based approach compared to the traditional deterministic approach based on one interpolated ore body model.

## A framework for managing geological risk

A framework of managing geological risk integrates three main elements:

1. ***Modelling geological uncertainty,***
2. ***Evaluating project risk due to geological uncertainty and***
3. ***Optimising decisions in mining under 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 by conditional simulation

Decisions in mining, such as equipment selection and specification, the optimisation of a short- or long term mine plan or the design of blending opportunities are usually based on 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 over the last two decades (Journel and Huijbregts, 1978; Goovaerts, 1997; Chiles and Delfiner, 1999; Dimitrakopoulos 2004). 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 realisation 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 2 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 behaviour does not represent reality. The two simulated models exhibit features inferred from data, namely the variability. Each realisation captures the global structure of the deposit but exhibits a different behaviour at a local scale. ▶

Analysing the spread of values from different realisations 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 discretised 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 (e.g. Journel and Huijbregts, 1978) or spectral methods (e.g. Borgman et al 1984; Pardo-Iguzquiza and Chica-Olmo, 1993) first generate unconditional simulations, which are conditioned by Kriging afterwards. This involves redundant computations and increases computational costs. Direct conditional simulation methods, such as sequential methods (Scheuer and Stoller, 1962; Journel, 1994) and conditional simulation via covariance matrix decomposition (Davis, 1987) perform the conditioning step during the simulation process. Dimitrakopoulos and Luo (2004) suggest the theoretical background for a computationally efficient method, the generalised 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 (2007) 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.

## 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 (Dimitrakopoulos, 1998; Dimitrakopoulos, 2004). Based on several equally possible ore body models the mining process or sequence of processes, such as open pit design or production scheduling, is conceptualised 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. ▶

**Simulation vs. Interpolation: geometry of coal seams and distribution of calorific value.**

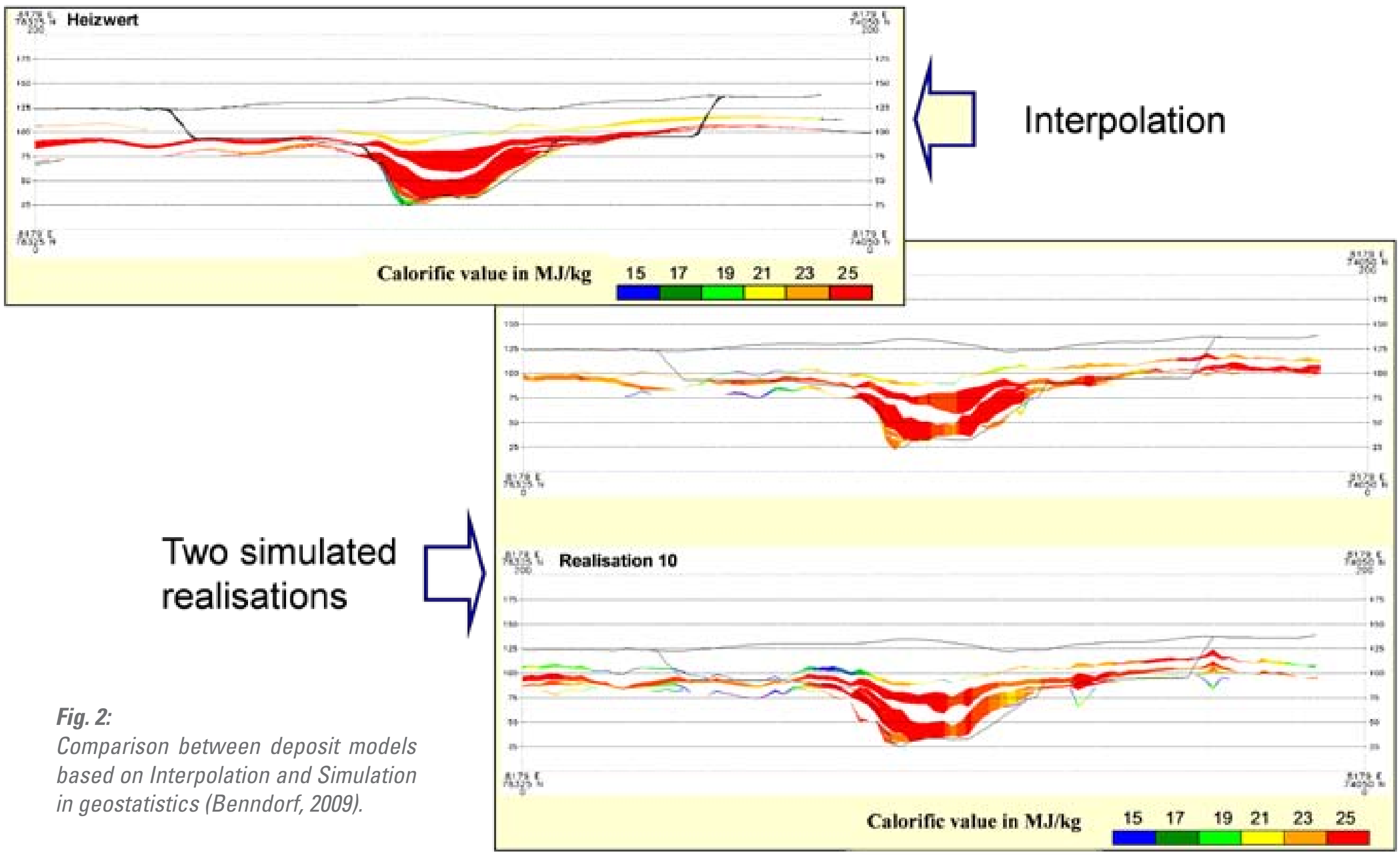



*Fig. 2:*
*Comparison between deposit models based on Interpolation and Simulation in geostatistics (Benndorf, 2009).*

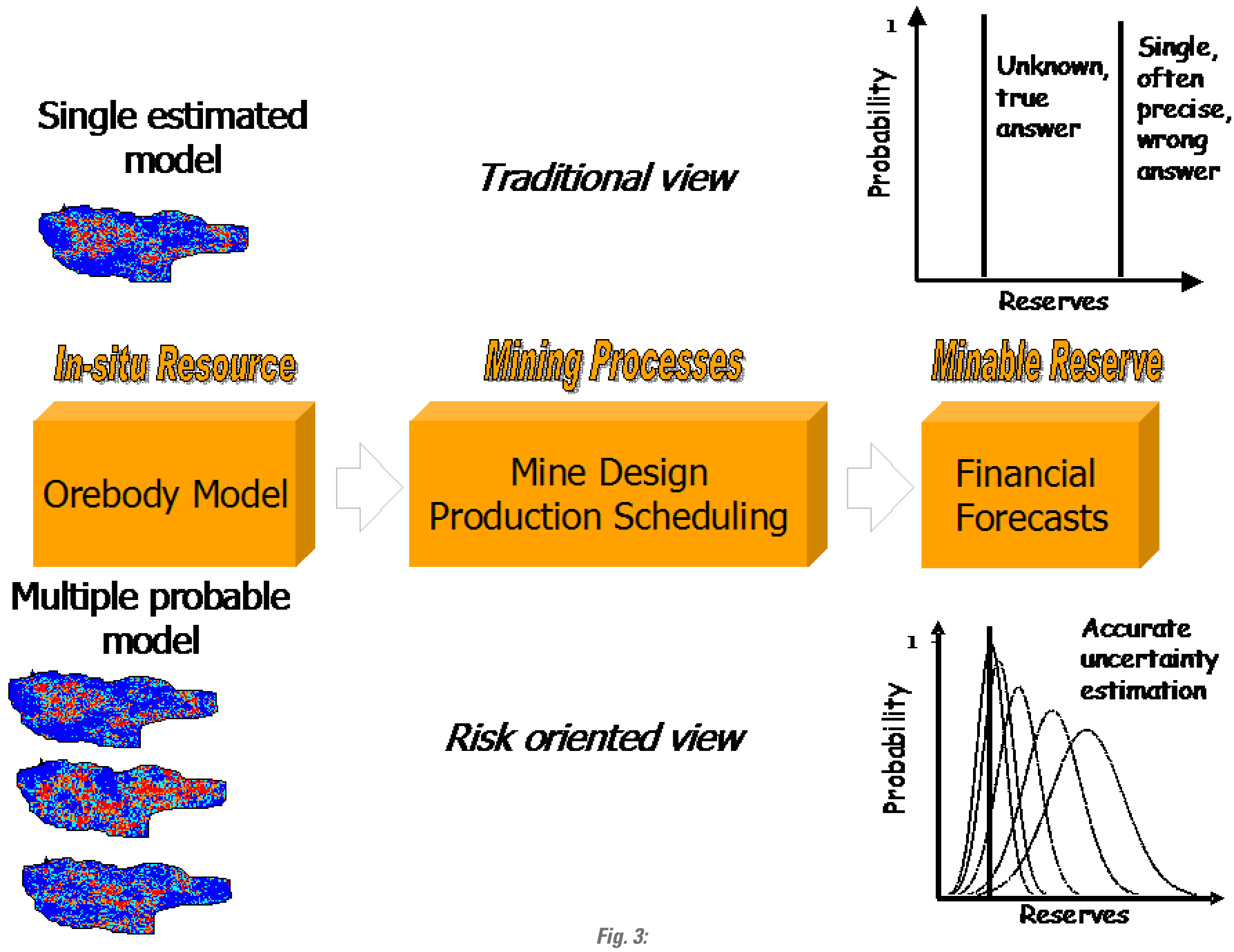



*Fig. 3:*
*General framework of modelling ore body uncertainty in mining (Dimitrakopoulos, 2004).*

Figure 3 illustrates the concept. It is important to recognise 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 in Benndorf (2009). For a given coal deposit with a defined level of exploration a mine plan was evaluated regarding its economic performance (Figure 4).

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 models to the evaluation procedure, a distribution of possible NPV's was generated as shown in figure 4.

Analysing 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". Variabilities, which are not captured in the interpolated model, cause 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.

Certainly interesting is the spread between Minimum and Maximum of 9.0 Mio Euro. 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 4 displays a typical diagram for optimising 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. Utilising 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 (JORC, 2004).

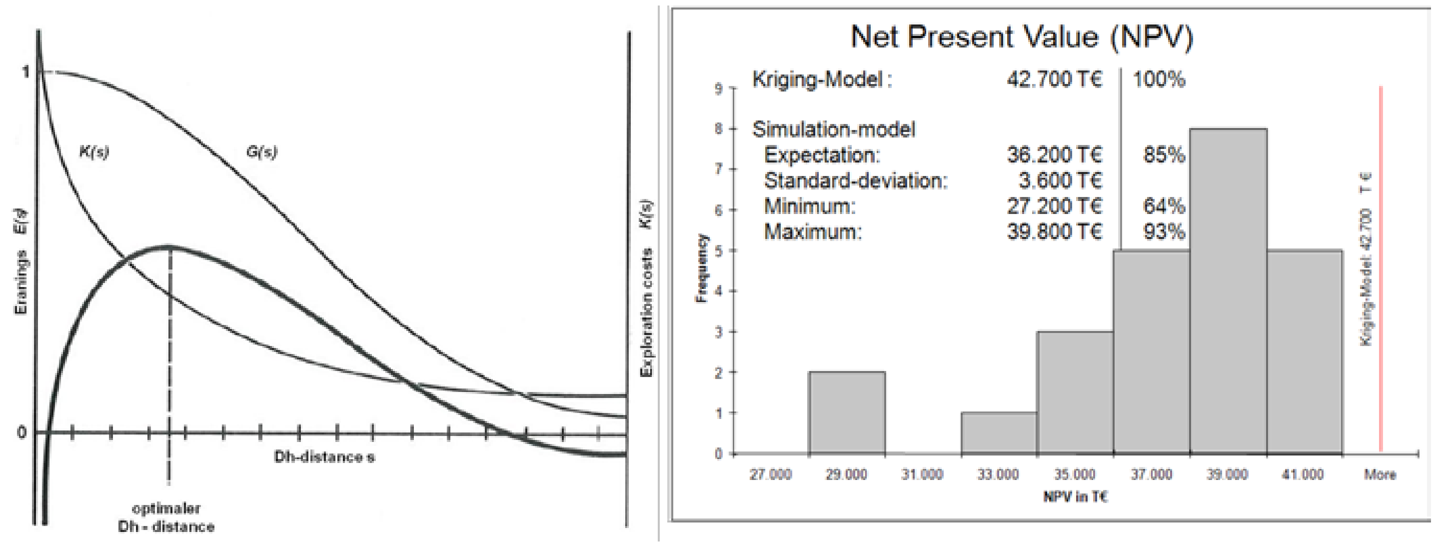
## Optimization of Mine Planning under geological uncertainty

Mine planning aims to define the "best" mining plan subject to the constraints imposed by physical and geological conditions, policies and the operational mining approach. The term "best" is defined by management objectives. These typically include maximising the monetary value of a mining project. An essential part of mine planning is production scheduling (Hustrulid and Kuchta, 1995).

It is concerned about the extraction sequence of parts of the deposit. Long-term production scheduling defines the sequence of mining phases, working fronts or pushbacks over the whole mine life with the goal to optimise the monetary value of the mining project. Restrictions are imposed by market and technological conditions.

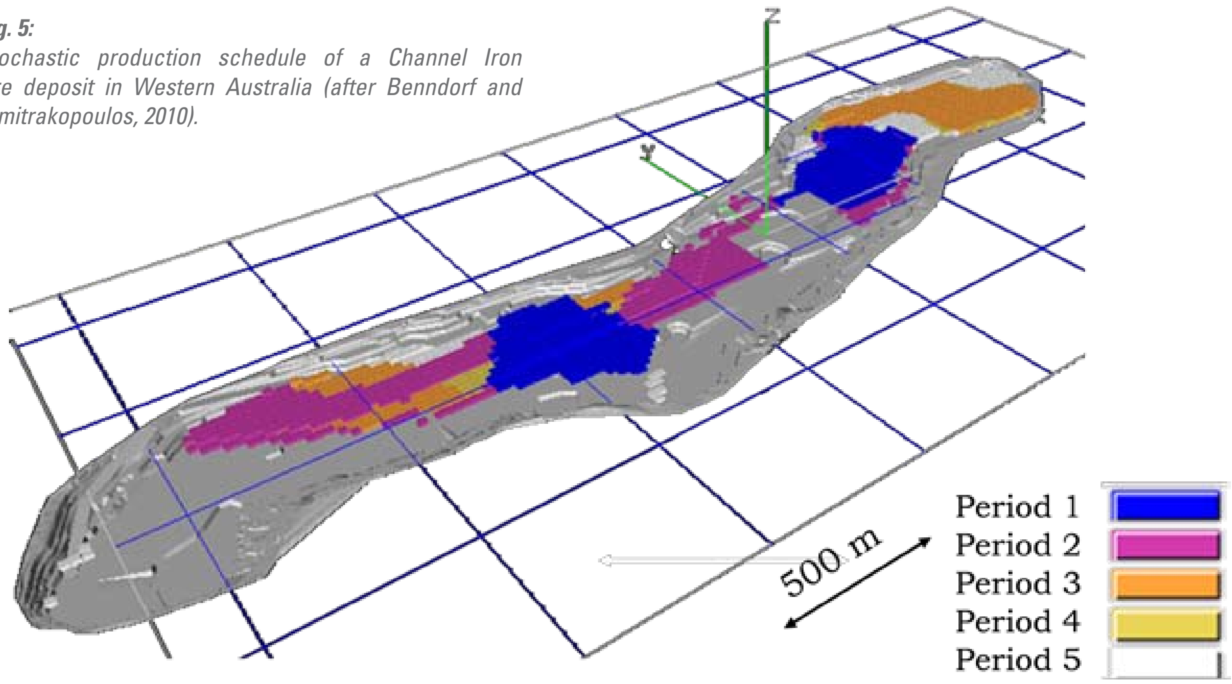
Production scheduling in mining ventures involving multi-element deposits, such as nickel, bauxite, coal or iron ore deposits, strongly depends on the ability to model and include the geochemical composition of the ore into the optimisation process. It influences the performance of the beneficiation process and the properties of the final product. In many mining projects often problems associated with high fluctuations in various quality parameters are reported. At the same time there is an increasing demand of output ore under strict market conditions. To minimize quality fluctuation and deliver a most homogeneous product, variability of key quality parameters should be adressed already in long-term production scheduling. Ramazan and Dimitrakopouos (2004) presented an approach to integrate modeled geological uncertainty into long-term production scheduling using stochastic integer programming (SIP). The goal here is to generate an extraction sequence that maximises the monetary value of the project while minimising the risk of deviating from production targets. This is achieved by integrating multiple simulated scenarios of the deposit into the optimisation algorithm. ▶

***Fig. 4:***
*Quantification of financial project risk due to geological uncertainty (right) and optimizing exploration strategy (left).*



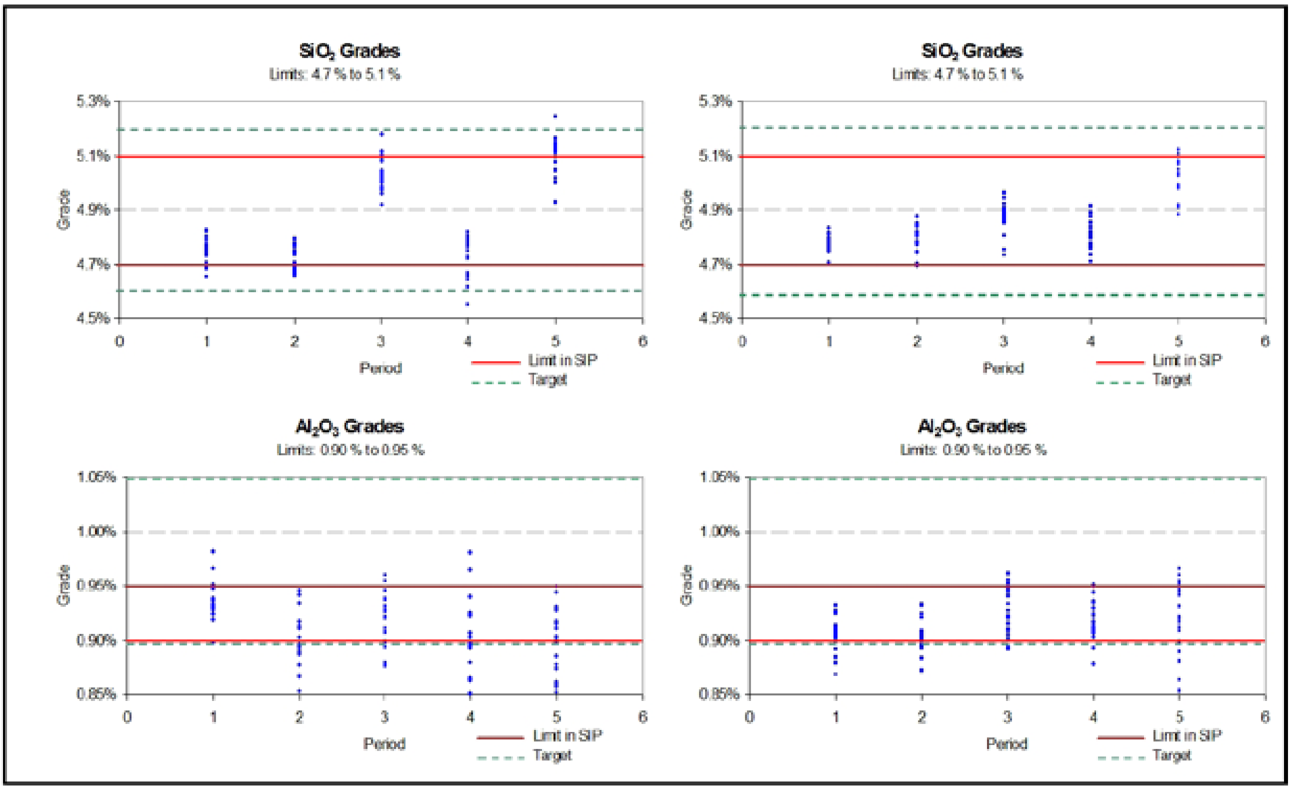
## Schedule

*Fig. 5:*
*Stochastic production schedule of a Channel Iron Ore deposit in Western Australia (after Benndorf and Dimitrakopoulos, 2010).*




Benndorf and Dimitrakopoulos (2010) applied the concept to an iron ore mine in Western Australia (Figure 5). The study considered production targets in terms of the different quality parameters SiO2 and Al2O3 and metal quantity. Results demonstrated the benefits of stochastic scheduling using simulations compared to the traditional approach using an interpolated model. Figure 6 shows the risk profile of meeting quality targets defined by maximum and minimum criteria per period for both schedules. ▶

*Fig. 6:*
*Risk profiles of SiO2 and Al2O3, per period for the traditional schedule based on an interpolated model (left) and the stochastic schedule using geostatistical simulation (right) (after Benndorf and Dimitrakopoulos, 2010).*



The traditional scheduling approach exhibits high fluctuations of the quality parameter, while the stochastic approach produces a schedule with significantly lower risk of deviating from targets. In addition, the economic benefit of the stochastic schedule was quantified with 35% less costs in penalties for deviating from targets compared to the one based on an interpolated model.

## Conclusions and future research

Understanding effects of geological uncertainty plays a key role in managing project risk in mining. A framework was presented that integrates modelling geological uncertainty, quantifying project risk and optimising decisions under uncertainty. The discussed examples demonstrate, how the framework can lead to a better understanding in geological uncertainty impacting financial performance. Besides the discussed cases the approach has high potential to improve decisions along the whole mining value chain, including optimization of drill-hole spacing, defining selectivities and selective mining units, equipment selection, short-term mine planning or stock-pile management.

The current trend in mining is moving towards more sophisticated applications of modern Information and Communication Technology (ICT) leading to a large amount of data along the whole extraction, transportation and beneficiation process. In addition to exploration data these data provide valuable information about the actual spatial behaviour of the resource and its impact to process efficiency and resource recovery. Future research will concentrate on capturing process data, back-propagation and integrating it into the resource and reserve model. Doing this in a real-time manner will provide the opportunity to identify deviations of the actual production from planning assumptions and take immediate action by optimising the process under the new conditions.

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