Quantification of Geological Uncertainty and Risk Using Stochastic Simulation and Applications in the Coal Mining Industry

S Li¹, R Dimitrakopoulos¹, J Scott¹ and D Dunn²

INTRODUCTION

Coal exploration, mine planning, economic valuation of coal assets, and coal production forecasting depend on the ability to effectively and reliably delineate, understand and assess coal resources and reserves. In turn, this ability supports investment decisions in exploration programs, development and production that are in the order of billions of dollars. Furthermore, Stock Exchange reporting of resources and reserves, aiming to benefit shareholders and attract the investment community, critically depends on the assessment of geological risk. Geological uncertainty is recognised as a critical factor in establishing accurate and reliable estimation, categorisation and economic assessment of coal resources and reserves, in terms of quality and quantity. Incomplete understanding of geological risk, including fault risk, is recognised as a major contributing factor to mining projects not meeting their financial expectations.

Stochastic simulation methods offer the technologies used to quantify geological risk. They are increasingly applied for this reason in metal mining and applications are widely reported (eg Dimitrakopoulos, 2004; Dowd, 1997; Ravenscroft 1992), including several papers in this volume. The practical application of simulation methods has been enhanced with the development of fast and efficient simulation algorithms better enabling the simulation of large, complex orebodies Benndorf and Dimitrakopoulos, 2004; Boucher and Dimitrakopoulos, 2004) and their integration with mine planning, design and production scheduling (Godoy and Dimitrakopoulos, 2003; Ramazan and Dimitrakopoulos, 2004; Menabde et al, 2004).

When compared to metal mining, there have been limited applications of stochastic simulations in the coal mining industry. Stochastic simulation is now being adopted, recognising the inefficiencies of traditional approaches to:

1. model coal seams based on drillhole information,
2. assign and classify coal resources,
3. establish drillhole spacing requirements for resource classification, and
4. identify the location of faults.

Two new developments in modelling geological uncertainty and quantifying the related risk with applications to coal mining are presented herein. The first development, extensively reported in Li, Dimitrakopoulos and Scott (2004) and Dimitrakopoulos, Li and Scott (2004), refers to the use of stochastic simulation methods to quantify risk in coal seams estimated with conventional methods, to assist Competent Persons in classifying resources and report the level of error with a given confidence. In addition, the approach developed provides the means to test the performance of drilling patterns and optimise data collection based on the local characteristics of the seam considered and a pre-specified error and confidence level. The second development, detailed in Dimitrakopoulos, Scott and Mackie (2001) and Li et al (2000), examines the simulation of fault systems and quantification of fault uncertainty. The performance of the approach in a back analysis study at a mined out part of a longwall coal mine elucidates the method and documents the performance of stochastic modelling, its advantages and characteristics.

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ABSTRACT

Stochastic simulation is a recognised tool for quantifying the spatial distribution of geological uncertainty and risk in earth science and engineering. Metals mining is an area where simulation technologies are extensively used; however, applications in the coal mining industry have been limited. This is particularly due to the lack of a systematic demonstration illustrating the capabilities these techniques have in problem solving in coal mining.

This paper presents two broad and technically distinct areas of applications in coal mining. The first deals with the use of simulation in the quantification of uncertainty in coal seam attributes and risk assessment to assist coal resource classification, and drillhole spacing optimisation to meet pre-specified risk levels at a required confidence.

The second application presents the use of stochastic simulation in the quantification of fault risk, an area of particular interest to underground coal mining, and documents the performance of the approach. The examples presented demonstrate the advantages and positive contribution stochastic simulation approaches bring to the coal mining industry.

QUANTIFICATION OF GEOLOGICAL UNCERTAINTY AND RISK IN COAL RESOURCE ESTIMATION AND CLASSIFICATION

The new JORC code (2004) requires that resource reporting be related to the level of geological confidence, that is, quantified geological uncertainty, for mining companies listed on the ASX. These companies and their Competent Persons are required to ensure that the resource computations and classifications comply with the basic JORC requirements of transparency, materiality and competency. Traditional approaches to the classification of resource have tended to use subjective criteria to define the limits of measured, indicated and inferred resource polygons. Existing guidelines encourage resource classification based on the maximum distances between drillholes and the number of holes drilled, without sound, scientific justification. The stochastic simulation approach to quantifying errors at a specified confidence interval in coal resource estimation to assist Competent Persons is presented next.

A methodology for risk quantification

The method proposed for quantifying risk involves the use of stochastic simulation to produce multiple coal resource models using all available drillhole data. With the simulated models representing the ‘actual’ deposit, a conventional orebody model can be assessed in terms of its ability to accurately predict reality. Figure 1 graphically illustrates the method. More specifically the method proceeds as follows:

1. W H Bryan Mining Geology Research Centre, The University of Queensland, Brisbane Qld 4072.
2. BHP Billiton Mitsubishi Alliance, Brisbane Qld 4000.
1. Generate a high-resolution coal deposit model (the ‘actual’ deposit) using stochastic simulation based on all coal seam data and geological information.

2. Reblock the points in the simulated coal deposit model to blocks of the same size used in the estimated seam model below.

3. Use a conventional method to generate an estimated seam model based on coal seam exploration data at the desired block size.

4. Calculate the relative absolute error of each block in the estimated deposit developed in step three by comparing it to the reblocked simulated deposit in step two. The relative error of a unit block $j$ is computed from:

$$
\varepsilon_{ij} = \frac{|v_{sij} - v_{ej}|}{v_{sij}} \quad (i = 1, ..., n; j = 1, ..., m)
$$

where:

- $\varepsilon_{ij}$ is the relative absolute error of the unit block $j$ with reference to the simulated deposit $i$
- $v_{sij}$ is the reblocked simulated value $i$ of the unit block $j$
- $v_{ej}$ is the estimated value of the unit block $j$
- $n$ is the total number of simulated deposits
- $m$ is the number of unit blocks within the study area

5. Repeat for a large number of simulated deposits (e.g., 50 simulations).

6. Summarise results graphically to illustrate the expected difference between an estimate and possible seam attribute values and the relationship between drillhole spacing.

The outcome of the above process is the spatial distribution of relative errors associated with the estimated coal resource model given the available drilling patterns and the block size considered. The program ‘GEOCOAL’ implements the above process (Li, Dimitrakopoulos and Scott, 2004) and is based on the sequential Gaussian simulation method (Dimitrakopoulos and Luo, 2004; Journel, 1994).

### A case study with coal seam thickness

The method described above is applied to a coal seam in central Queensland, Australia, to demonstrate how geological risk can be quantified in a practical situation. Figure 2(a) shows the coal seam thickness data in the study area, and Figure 2(b) shows one of the simulated models of coal seam thickness on a dense grid corresponding to step one of the method described above. Figure 3(a) shows the estimated coal seam thickness model for 50 by 50 m blocks from step three of the method above. The relative error associated with the conventional model is based on the estimated model and the reblocked simulated deposits using the formula given in step four above. Figure 3(b) shows the spatial distribution of the relative errors associated with the conventional coal seam thickness model. It is important to note that the confidence level for the relative errors shown is 95 per cent, and is derived numerically from the use of multiple simulated seam scenarios.

The quantified errors derived by the method used here reflect both the drillhole spacing as well as the in situ variability of the coal seam. For example in Figure 3(b), the relative errors in the upper left section tend to be higher than those in the lower part of the seam (between ten per cent and 20 per cent) due mostly to the sparser drilling in that part of the study area. The lower part of the study area shows relative errors less than five per cent and, although denser drilled, these low errors mostly reflect the local low variability in coal seam thickness. It is clear that these two areas of the coal seam will require different drilling densities to generate the same level of errors at the same confidence level. Similarly to thickness, any other attribute of the coal seam can be modelled and errors assessed.
Extending the method to optimise drillhole spacing

The method presented above can be extended to assess the value of drilling campaigns before the drilling is conducted. The quantification of expected errors in estimates ahead of actual drilling would reduce over- and under-drilling. Desired criteria, such as the increase of expected confidence levels sought in resource estimates can be tested. For example, a drilling campaign can be designed to generate errors on estimates that are expected to be +/-10 per cent at a 95 per cent confidence level.

In practice, alternative drilling patterns are designed, and all simulated deposits generated previously are sampled. The virtual samples are then used exactly as real data in the error quantification process previously described. Figure 4 plots the average relative errors of seam thickness associated with selected drilling densities (200 × 200 m², 300 × 300 m², 500 × 500 m², 800 × 800 m² and 1000 × 1000 m²) for the same seam and study area shown earlier. The overall relative error of seam thickness associated with each drillhole spacing pattern up to 500 × 500 m² is less than five per cent at the 95 per cent confidence level, reflecting a general regularity in seam thickness. If an error of estimation less than ten per cent with a 95 per cent confidence is required, then the seam should be drilled at spacings over 1000 × 1000 m².

Figure 5 shows the spatial distributions of errors for two experimental drillhole spacing designs, 500 × 500 m² and 800 × 800 m², in the same study area with 95 per cent confidence levels. The estimation errors at the upper left in both Figure 5(a) and (b) are higher than those at the lower right, which is likely due to the higher seam variability in this area. This example
graphically illustrates how the method proposed here can assist in identifying parts of a study area that may require a different spacing. More specifically, if for example an error less than ten per cent at 95 per cent confidence is needed, the drillhole spacing in the upper part of the area shown in Figure 5 should be, at most, 500 × 500 m², whilst the drillhole spacing in the lower-right part need not be less than 800 × 800 m².

QUANTIFICATION OF FAULT UNCERTAINTY

A companion aspect to the uncertainty modelling of quantity and quality parameters of coal seams, as well as geological risk quantification for resource classification, is geological uncertainty and risk due to structural deformation. Faults are a major factor impacting particularly underground longwall mining. Unlike the so-called continuous parameters of coal seams that are stochastically simulated with a variety of methods for continuous variables (e.g., Dimitrakopoulos, 2004), faults are ‘discrete’ objects and require the development of complex approaches, such as the one described in Scott et al. (2004). The approach is based on fractal fault size distributions and length-throw statistical relations, combined with a probability field approach to ‘thinning’ a Poisson process so as to locate fault centres. The following sections visit this method in a ‘back-analysis’ case study that assesses the performance of the specific method and provides an insight to the stochastic simulation framework.

Stochastic simulation of faults and field testing

To assess the above-mentioned fault simulation method, a fully mined part of a longwall mine is used. Two data sets are formed:

1. the complete data set available, used as the ground truth to assess the fault simulation method; and
2. a subsample of this data set that resembles the level of fault mapping and information available at the time of the longwall design from ‘exploration’ sources (referred to here as the ‘exploration’ data set); this ‘exploration’ data set is used to generate statistics of fault population characteristics and simulate fault populations.

Figure 6(a) shows the complete fault data set in the mined out part of the corresponding longwall mine, and Figure 6(b) shows the ‘exploration’ data set.

Two simulated fault populations using the ‘exploration’ data set are shown in Figure 7. The simulated fault populations reproduce the faults in the data set in Figure 6(b), and honour the fault characteristics derived from this ‘exploration’ fault data set; such as fractal characteristics, the power-law relationship between fault length and throw, and the fault strike distributions (Dimitrakopoulos et al., 2001). In comparing the simulated fault populations with the complete data set shown in Figure 6(a), the similarity between the simulated fault population and the complete fault data is evident, both in terms of the spatial distribution and density of faults.

A set of 50 simulated fault populations based on the ‘exploration’ data set is used to generate the fault probability map shown in Figure 8(a). Figure 8(b) shows the fault probability based only on the faults in the ‘exploration’ data set (70 faults with throw ≥1 m) and Figure 8(c) illustrates the fault probability using the complete data set (231 faults with throw ≥1 m). The conventional approach used for assessing or designing a longwall mine considers ‘exploration’ data sets only, resulting in the underestimation of actual fault risk. In contrast, the fault probability map based on 50 simulated fault populations corresponds to about 207 faults with throw ≥1 m and provides a realistic assessment of risk when compared to the true fault risk.
FIG 6 - (a) Complete mapped fault dataset from the mined out part of a longwall mine; (b) ‘exploration’ fault dataset, a subsample of the complete data set (faults shown have a throw ≥ 1 m).

FIG 7 - Two fault realisations using the ‘exploration’ fault dataset (faults shown have a throw ≥ 1 m).
Locations denoted by a ‘1’ in Figure 8 indicate areas that have been accurately predicted to have a high fault risk. Locations denoted by a ‘2’ are where the fault simulation method overestimates risk. Locations denoted by a ‘3’ are where the fault simulation method has slightly shifted actual high-risk areas.

The example presented here provides a positive assessment in using simulation methods. Its ability to generate a more realistic assessment of fault risk than the spatially limited and incomplete exploration data set alone is apparent.

Integrating fault risk to resource classification

The ability of the above simulation approach to provide a realistic assessment of fault risk has ramifications to coal mining. One of these is the integration of quantified risk from different sources with respect to resource classification. It is relatively simple to combine assessments of resource risk as discussed earlier, such as coal resources estimation errors and fault probabilities. For example, Figure 9(a) shows the error map in coal tonnage in a lease and Figure 9(b) shows a map of the probability of faulting. Figure 9(a) indicates that estimation errors in coal tonnage are less than 20 per cent over the study area. If a threshold of 20 per cent were used for measured resources, the entire study area would be classified as a measured coal resource. However, Figure 9(b) shows that the fault probabilities in sections A, B, C, D and E are as high as 100 per cent and these sections should therefore be excluded from the measured resource classification. Conversely, in sections F and G the fault probabilities are between ten and 30 per cent implying that the coal resources in these sections could be measured rather than indicated, pending further drilling for fault detection. An alternative approach may be to consider assigning dollar values to different fault probabilities such that sections with a high probability of faults are assigned the highest cost of mining. This leads to the discounting of the value of a coal resource based on fault risk and allows coal resource classification to incorporate faulting information.

CONCLUSIONS

Stochastic simulation methods can assist in addressing the quantification of geological uncertainty adversely impacting various aspects of coal mining, including resource classification, drillhole spacing optimisation and quantitative fault risk assessment.

Two broad areas of applications in coal mining were presented. The first area refers to:

1. the quantification of uncertainty in coal seam attributes and risk assessment that can assist mining companies and their Competent Persons with resource classification; and
2. the application of quantified geological risk to the optimisation of drilling patterns to meet the desired risk level with the required confidence.

The simulation method presented provides a transparent and defendable approach to resource classification and provides a way to assess the drilling that may be required to generate models with a given error and confidence level.

Fig 8 - (a) Fault probability map based on 50 fault realisations; (b) fault probability map based on the ‘exploration’ fault dataset; and (c) fault probability map based on the complete and mapped fault dataset; all faults shown have a throw ≥1 m.
The second application presented involved the stochastic simulation of fault systems and related quantification of fault risk. The work presented showed a back analysis study that demonstrated the ability of the fault simulation approach to quantify and assess fault risk. Quantification of fault risk can assist resource classification and be integrated with the simulation of other coal seam attributes.

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REFERENCES


Fig 9 - (a) Errors in coal tonnage and (b) faulting probability map in a coal lease, and joint consideration to assist coal resource classification.


