Quantification of Risk Using Simulation of the Chain of Mining—Case Study at Escondida Copper, Chile

S. Khosrowshahi, W. J. Shaw and G. A. Yeates

Abstract Quantification of risk is important to the management team of any rapidly expanding mining operation. Examples of areas of concern are the likelihood of not achieving project targets, the impact of a planned drilling program on uncertainty and the change in the risk profile due to a change in the mining sequence. Recent advances in conditional simulation and the practical use of such models have provided the opportunity to more fully characterise mineral deposits and to develop empirical estimates of the recoverable resources and ore reserves. This allows meaningful quantification of risk (and upside potential) associated with various components of a mining project. This paper presents an approach referred to herein as 'simulation of the chain of mining' to model the grade control and mining process. Future grade control sampling, mining selectivity and other issues that impact on the final recoverable tonnes and grades are incorporated. The application of this approach to Escondida, a large-scale open pit copper mining operation in Chile, provided a definitive way to assess the expected risk of a number of alternative development strategies on operational performance of the project. This approach is gaining acceptance as one of the most important steps in developing short-term mining models. The concepts developed here also have implications for assessing the ore that will be recovered from ore reserves during mining.

S. Khosrowshahi (✉)
MAusIMM(CP), Golder Associates, Level 2, 1 Havelock Street,
West Perth, WA 6005, Australia
e-mail: sia@golder.com.au

W. J. Shaw
FAusIMM(CP), Ore Control, Perth, WA, Australia
e-mail: bill.shaw@orecontrol.com

G. A. Yeates
FAusIMM(CP)— BHP Limited, 86A, 3001 Melbourne, Vic, Australia
e-mail: gavin.yeates@bhpbilliton.com

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Introduction

The Escondida open pit copper mine is located 140 km south east of Antofagasta, Chile. The mine started production in the late 1990s and by 2004 the annual production reached 82.4 Mton of sulfide ore; generating 1,005,200 ton of copper concentrate, 152,300 ton of cathode copper, 179,800 oz of gold and 4.5 Moz of silver. The orebody is a porphyry copper formed by two major stages of sulfide and one stage of oxide mineralisation. The supergene enrichment blanket of the deposit is defined by chalcocite and minor covellite with remnant chalcopyrite and pyrite that reaches a thickness of several hundred metres in places. The largest contributor of mineralised tonnage in the deposit is an Oligocene porphyritic intrusive hosted by andesites, combined with less significant hydrothermal and igneous breccias occurring throughout the deposit.

This study was conducted to assess the risk associated with the use of the Escondida resource model as a basis for developing mine schedules, forecasts and budgets of mineable ore. In addition, it was used to define the impact of risk for the first five years of the Phase IV Expansion and identify the alternative mine schedules that present less risk. The study was based on the construction of a large conditional simulation model, covering a significant part of the Escondida copper mine and the analysis of this model through a 'transfer function' or mining process termed the Chain of Mining (CoM).

More specifically, a geostatistical conditional simulation (CS) model was developed for a large part of the Escondida sulfide resource that contained five years of scheduled mining from the start of year one to the end of year five. The CS model consisted of 50 realisations that independently defined the lithology (andesite or non-andesite), the mineralisation zones (High Enrichment, Low Enrichment and Primary) and the grade (per cent copper as total copper and soluble copper) dependent on the previous two geological variables. A Chain of Mining approach was then used to model the errors impacting upon the translation of the in situ resource to a recoverable ore reserve. A number of CoM models were developed and analysed to determine the parameters that would match actual mining performance at Escondida. The impact of various contributing errors was modelled using parameters for blasting movement, sampling and assaying precision, sampling and assaying bias, and mining selectivity. The CoM models were examined in relation to all available reconciliation results. From available production data it was evident that the Escondida resource model available at that time significantly over-predicted the tonnage that was realised during mining. A base case Chain of Mining model was selected that appeared to best capture the real performance indicated by the production data. This case was used to predict the performance of the current mining practice within the volume defined by the planned next five years of mining. The analysis was done on a quarterly basis and a pushback basis for two alternative (north and east) mining options.

The approach presented herein is based on sequential conditional simulation (e.g. Journel and Huijbregts 1978; Goovaerts 1997; Benndorf and Dimitrakopoulos

2017, this volume; Nowak and Verly 2007, this volume) and the concept of 'future' grade control data for recoverable reserve estimation detailed in Journel and Kyriakidis (2004). Related aspects are discussed in the next sections, which start with the description of available data and conditional simulation modelling at Escondida, followed by the CoM approach (Shaw and Khosrowshahi 2002), a calibration of the resulting models and a comparison with production. Conclusions and comments follow.

Data and Data Analysis

Data sets used for analysis were based on 15 m bench composites for exploration data and grade control data. Subsequent analysis was based on the High Enrichment (HE), Low Enrichment (LE) and Primary (PR) zones. The lithology was considered as two domains, Non-Andesite porphyry/breccia and Andesite. Thus, there were six modelling domains for preliminary analysis, including univariate statistics of exploration and grade control data for total copper (CuT) and soluble copper (CuS).

To assess continuity trends for the characterisation of anisotropies in the data prior to variography, maps of grade and grade indicators were constructed. The interpolated maps were not constrained by the lithology or mineralogical zones and, therefore, reflect an isotropic interpolation of the data in 3D. The maps were used for the preliminary identification of grade continuity trends in order to further the definition of domains and for variographic analysis. The plan view maps indicated different grade continuity trends on either side of the north–south line at 16,300 E. On the eastern side, grade continuity has a NE orientation. This differs from the western side, which shows a NW continuity. An indicator defining the samples coded as andesite or non-andesite was also mapped in the same way.

Variography of the exploration and grade control data sets for total copper and for the ratio of soluble copper to total copper (ratio) was carried out for each of the HE, LE and PR mineralogical zones with subdivision by lithology (andesite and non-andesite, i.e. porphyry) that was separated into east and west at 16,300 E. Preliminary variograms of exploration data did not provide a good definition of short-scale structures. This is mainly due to the exploration data density, which does not allow accurate and detailed variogram definition over small distances. The exploration variograms generally characterised large-scale structures, but these are not as critical to risk assessment as the characterisation of short-scale continuity. It was found that variograms of grade control data generally showed less continuous behaviour, and a far clearer definition of short-scale variability. Accordingly, it was decided to model variograms of grade control data for all domains containing sufficient data to characterise this short-scale variability for simulation purposes. Exploration variograms were also modelled to determine the sensitivity of the study to this approach. For the Primary zone, grade control data was scarce and the variograms were based on exploration data, although this generally produced poorly defined variograms for the west domains.

The enrichment surfaces were based on the HE, LE and PR codes in the exploration and grade control data (Fig. 1). For this analysis, it was considered necessary to use a combined grade control and exploration hole surface data set for each of HE, LE and PR for variographic purposes to ensure that maximum coverage was provided of the spatial data.

Generation of the Conditional Simulation Models

First, the enrichment surfaces were simulated using sequential Gaussian simulation, followed by the simulation of the two lithologies, andesite and non-andesite, using sequential indicator simulation. These models were merged resulting in simulated models, each with its own lithology and enrichment surface. Next, these models were populated with simulated CuT and CuS grades.

Simulation of the Enrichment Surfaces

An example of the final simulated enrichment surfaces are provided in Fig. 2. The influence of the conditioning data is evident when comparing the simulated images of the HE, LE and PR surfaces. The lower number of conditioning data points for the PR surface leads to greater variability in the simulated surface. Variography was carried out for the mineralogical contacts described by the geological interpretation (enrichment surfaces). Variography of the surfaces was performed in 2D (Fig. 3) with the variable analysed being the RL coordinate.

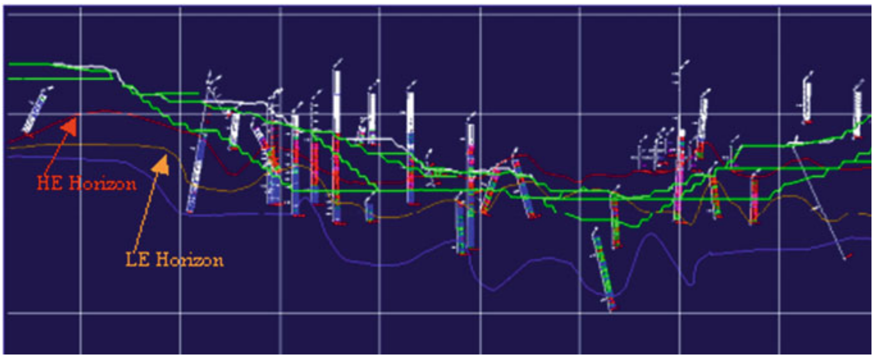

Fig. 1 Typical cross-section at escondida copper

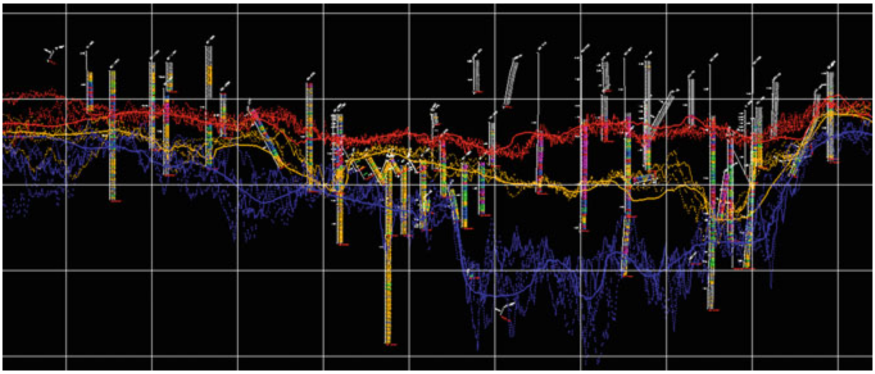

Fig. 2 Example of simulated image of the enrichment profiles

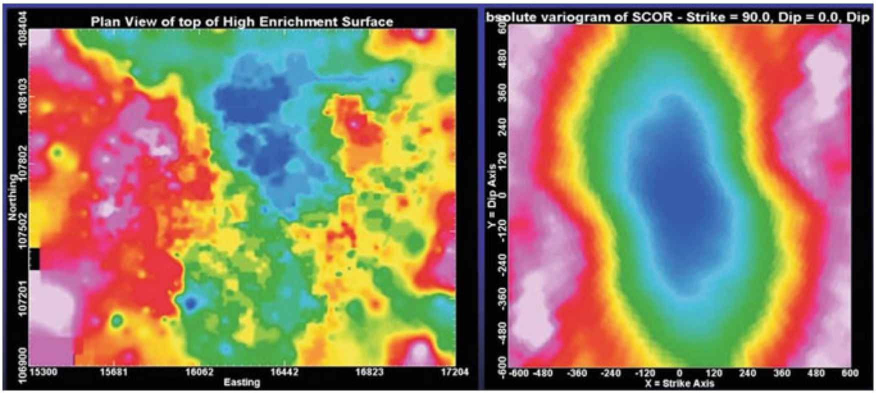

Fig. 3 Example of high enrichment elevation contour and associated variogram map

Simulation of Lithological Data

The dominant rock type for the Escondida deposit is porphyry. Grades in the andesite west of the 16,300 coordinate line are generally recognised to be lower than those in the porphyry lithologies and metallurgical recoveries are lower. The data was examined and it was decided, for the purpose of this study, to define two lithologies, namely andesite and non-andesite (or porphyry), which is used for porphyry/breccia and all other non-andesite lithologies. The lithology variography was based on indicators for andesite (and porphyry) for all data below the top of the HE zone. The indicators were defined from the drill log codes in the grade control and exploration data sets. As for the grade variography, the lithology variography was carried out for separate populations east and west of 16,300 E.

The lithological data was simulated as a categorical variable (Fig. 4). The presence of andesite was defined in the drill hole data using an indicator value of 1

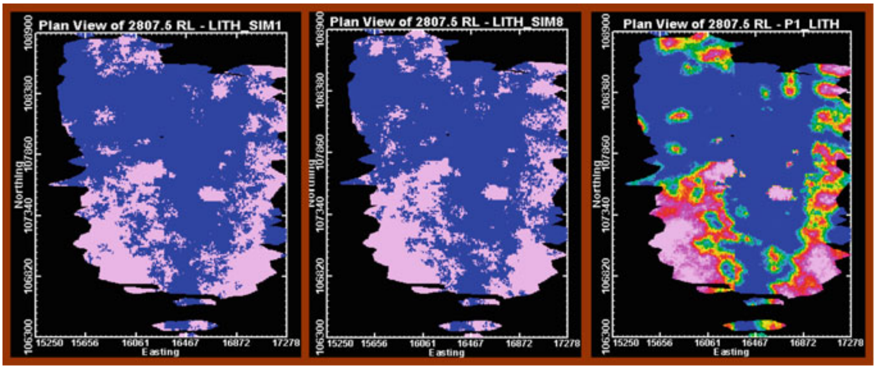

Fig. 4 Various simulated lithological data with associated probability map

with the absence of andesite (i.e. the presence of porphyry) assigned an indicator value of 0. The conditioning data set used for simulation of this categorical variable was the 15 m composited exploration data combined with the grade control 15 m blasthole data. The coded lithology data and the indicator variogram parameters were used to generate a sequential indicator simulation 3D model of the lithology as defined by the distribution of the andesite indicator.

Generation of the Geological Conditional Simulation Model

The 50 two-dimensional simulated realisations of each of the three enrichment surfaces and the 50 three-dimensional simulated realisations of andesites in two separate domains (east and west) were then merged into a single geology conditional simulation model comprising all simulated outcomes. Thus, there were 50 simulations each with a different lithology and Minzone outcome (Fig. 5).

Simulation of Grades for CuT and CuS

Twelve separate domains were considered for simulation of the percentage of copper as CuT and CuS grades. The conditioning data for each domain was the 15 m exploration composite data set. For each domain, appropriate data belonging to that domain was extracted. The sequential Gaussian simulation approach was used to simulate grades (Fig. 6) and simulated realisations for each domain were validated by checking the reproducibility of the weighted histogram of the exploration data, and the normal score variogram model from the grade control data.

It is impossible to produce a perfect representation of any deposit as a resource model since the geological knowledge, the sampled data, and the assumptions made

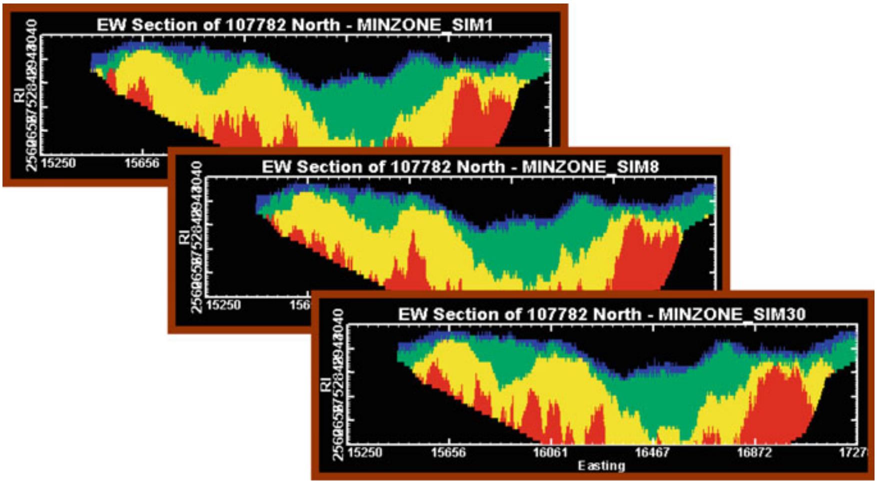

Fig. 5 Example of combined simulated geological data

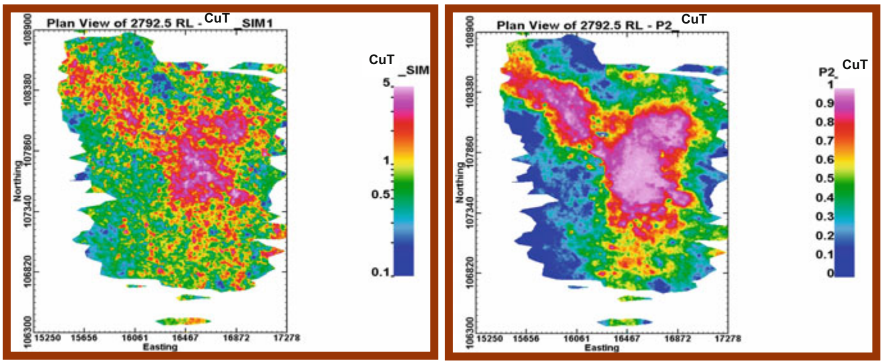

Fig. 6 Typical simulated image for CuT and associated probability map

during estimation are all imperfect. If a model was perfect it could be used as the basis for mining without any requirement for further mapping or sampling. Collectively, these imperfections are termed the *information effect* and can never be overcome completely. During mining, decisions are made based on similar imperfect data. Geological mapping, sampling and assaying are used to provide a basis on which the ore boundaries are defined and mined. Estimates of grades within the ore blocks must be made from the best available data. The impact of such estimates causes dilution (material below the cut-off grade being sent to the mill) and ore loss (ore incorrectly being sent to low grade stockpiles or waste dumps). Imperfect knowledge of the deposit again plays a part, but to this is now added imperfect mining practices. Even if the cut-off grade boundary could be defined perfectly it could not be mined perfectly every time at a practical mining scale.

To differentiate between the impact on resource modelling and the impact on mining, these imperfections are collectively termed the *grade control effect* and, again, can never be overcome completely.

The Chain of Mining Approach

For any measurable value, the term error can be used to indicate the difference between an estimate and the true value. During the process of defining an ore block for mining, a number of measured values are used, such as the location of the ore in 3D space, the representativity of the sample, the quality of the sample, the grade of the sample, and the cut-off boundary of the ore block boundary to be mined. For each of these attributes a 'true' value and an 'estimated' value can be defined.

Mining decisions are in all cases based on the estimated value. However, the results of mining are in all cases determined by the true value. For example, the placement of an ore block boundary and the predicted grade of that ore block might be defined solely by the sampled grades in and around that block. Errors in the sampling process (which leads to imperfect delineation of boundaries) and during mining (which leads to imperfect mining of the planned boundaries) both result in dilution and ore loss such that the grade of the ore delivered to the mill is invariably lower than that predicted by the estimated values. This is because the application of a cut-off grade alters the impact of the distribution of errors. Waste incorrectly sent to ore is by definition always of lower grade than ore incorrectly sent to waste.

There are various approaches that can be taken to solving this nexus between 'predicted' and 'actual' mining performance. For the present study, a series of parameters that model the differences between the predicted and actual mining performance were measured. To define these parameters, the various stages where errors can occur in measured values were considered. The mining process as a whole was considered to be a chain of events with the consequences of each event impacting on the next measurement in sequence. The term Chain of Mining is used to underscore the dependence of the eventual mining result on each link in the process (Shaw and Khosrowshahi 2002; Shaw et al. 2002; Khosrowshahi and Shaw 1997). Figure 7 provides a schematic of the process to characterise the generation of recoverable resource estimates.

Sources of Error During Mining

It was apparent that there were four possible sources of error that contributed to the grade control effect and which could be modelled, namely, sampling and assaying errors of precision, sampling and assaying errors of bias, movement due to blasting as lateral displacement or heave, and mining selectivity. It was recognised that it would be impractical to attempt to define parameters in detail for every possible

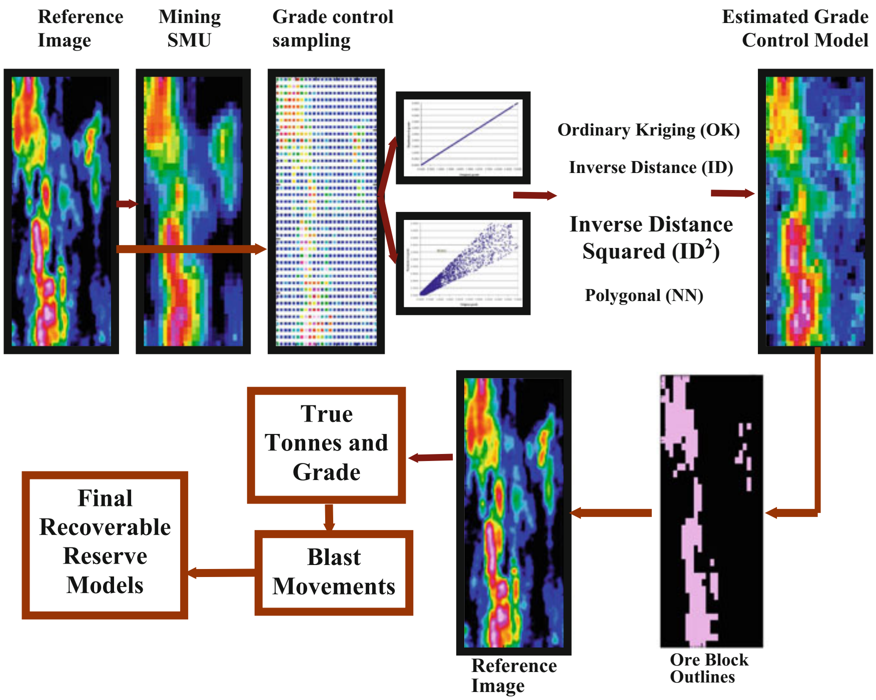

Fig. 7 Using the chain of mining process on a simulation model to characterise recoverable reserve estimates

source of error at Escondida. In addition, due to the large and very complex nature of such a mining operation, there is always the possibility that one or more practices will change in time. Instead, an empirical approach was taken. Error models were developed where observation on site indicated that this would be appropriate and these various error models were tested to determine their impact.

Error Due to Sampling and Assaying Precision

The grade control sampling at Escondida is done using vertical blastholes. The ore is blasted and dug on 15 m high benches. The blastholes are drilled with large rotary air blast equipment, drilled to a depth of 15 m (one mining bench) plus subdrill of approximately 2.5 m. Sampling errors that will lead to a difference between the actual grade of the material in the cone of blasthole cuttings and the true grade of the ore in the ore block are not quantifiable (since they are frequently not repeatable). Nevertheless, these errors exist and include both the sample delimitation error due to subdrill material remaining in the cuttings cone, and sample extraction error due to contamination and loss during the open hole rotary drilling, and due to dust loss.

The subsampling of the spoil cone is done manually after drilling using a tube sampler and eight increments are collected. The sample is then further crushed and subsampled in the MEL site laboratory. The errors that impact on the predicted grade include:

1. the grouping and segregation error that is due to splitting of the spoil cone (in this case due to the tube splitter); and
2. error due to the relationship between particle size and grade, known as the Fundamental Sampling Error (Gy 1979) that results from the process of splitting, crushing and pulverising to reduce the 2 t sample spoil cone to a 200 g pulped sample submitted for assay.

The first type of error is not quantifiable, and every subsampling system incurs the second type of error. The total impact of all these errors was modelled in two scenarios:

Low Sampling Error

A relative sampling precision of ±20% was assumed as the base case. This incorporates the measured precision of ±10% demonstrated by repeat sampling and assaying of blasthole cones (Fig. 8). An allowance for additional error was made due to the drill sampling method. This scenario assumes high quality grade control sampling is available.

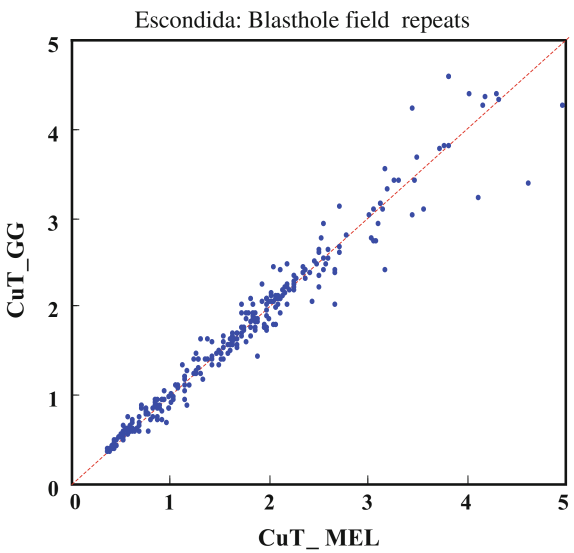

Fig. 8 Field duplicates of escondida blasthole cone sampling from which a relative precision of ±10% was obtained

High Sampling Error

A relative sampling precision of ±60% was assumed as the high error case to indicate the typical level of sampling repeatability that occurs in twinned blasthole drill sampling. No data for this estimate was available. The nearest such data was paired blasthole and resource hole estimates where a precision of ±40% was obtained. The high error case was adopted to allow for the impact of the blasthole subdrill and accounts for the local variability typically seen in blasthole sampling.

Error Due to Blasting

Ore movement can result in the predicted ore being displaced so that the material eventually mined is different from that which was planned. The degree of dilution and ore loss that this causes is dependent on the lateral displacement of the ore block boundaries, and the vertical heave resulting in mixing across horizontal mining levels. Heave is not an issue at Escondida since the ore is blasted and mined on a single mining bench. It was decided to model two scenarios, one where the lateral blast movement was negligible and one where the movement was 3 m in both the east-west and north-south directions, this being the movements observed on site for a number of blasts.

Mining Selectivity

Perfect mining of any orebody is always impossible due to two factors; the availability (and quality) of data to define boundaries, and the ability of the equipment to dig a defined boundary, which decreases with the production scale of the operation. The effective minimum mineable block size can be expected to relate in some way to these factors and, consequently, in a resource model the point estimates of grade, interpolated from drill hole (quasi-point) data, may be aggregated to a mineable block size.

The degree of mining selectivity represented by a resource block model is defined as the selective mining unit (SMU). This SMU block size may be regarded as the minimum viable size of a mining block, although of course, the average size of the mined blocks may be much bigger. The degree of misclassification that generally occurs along any block boundary during mining is directly related to the production rate and size of the mining equipment. The concept of the SMU block size can assist in understanding the impact of the mining method on the orebody and how well this can be represented by the resource model.

Calibration of the Chain of Mining Models and Comparison with Production

The conditional simulation model developed for the Escondida deposit was used to test the impact of various mining selection parameters and the impact of the various expected errors. A series of ten cases was developed using the parameters defined in Table 1 to address misclassification errors likely to arise during mining. These CoM models were then tested against production records and compared to the Escondida resource model.

Analysis of the results for the different scenarios indicated that Case 6 (presented in bold in Table 1) was the closest to the Production data total of 100,294 Mt at 2.11% CuT. The selected case used no blasting movement, a high sampling error consistent with blasthole samples, and an 8 × 8 m SMU block area. The smaller SMU size provided better selectivity at the cut-off grade, producing a lower tonnage and higher grade than that predicted by the resource model. Case 6 was regarded as the base case. Various models were intersected with each wire-frame defining the mine plan, and the results were aggregated by both quarterly period and major pushback increment. For the Chain of Mining cases, each of the 50 simulations was separately intersected with each wire-frame to provide a risk profile of the chance of not achieving the scheduled tonnes and grade for the period that the wire-frames represented. The tonnages and grades within each simulation realisation were determined for the quarterly and pushback increments for the base case (8 × 8 m SMU with high sampling error). The results are presented in graphical form in Figs. 8, 9, 10, 11 and 12. In assessing the relative risk using this graphical data, occurrences below the horizontal line indicate where the expectation of tonnes or grade was not reached, i.e. periods when the resource model is at risk under the assumed mining scenario.

Table 1 Parameters used in the chain of mining (CoM) analysis for the various CoM models examined, with results for the reconciliation period

Case	Blasting movement	Sampling error	SMU (15 m high)	Mt	Grade % CuT	Comment
1	0	Low	16 × 16	109.4	1.875	
2	0	Low	8 × 16	107.5	1.893	
3	0	Low	8 × 8	103.3	1.929	
4	0	High	16 × 16	108.0	1.885	
5	0	High	8 × 16	105.3	1.907	
6	**0**	**High**	**8 × 8**	**99.0**	**1.953**	**closest to mine production data**
7	3	Low	16 × 16	109.4	1.861	
8	3	Low	8 × 16	107.5	1.873	
9	3	High	8 × 16	105.3	1.887	
10	3	High	8 × 8	99.0	1.921	

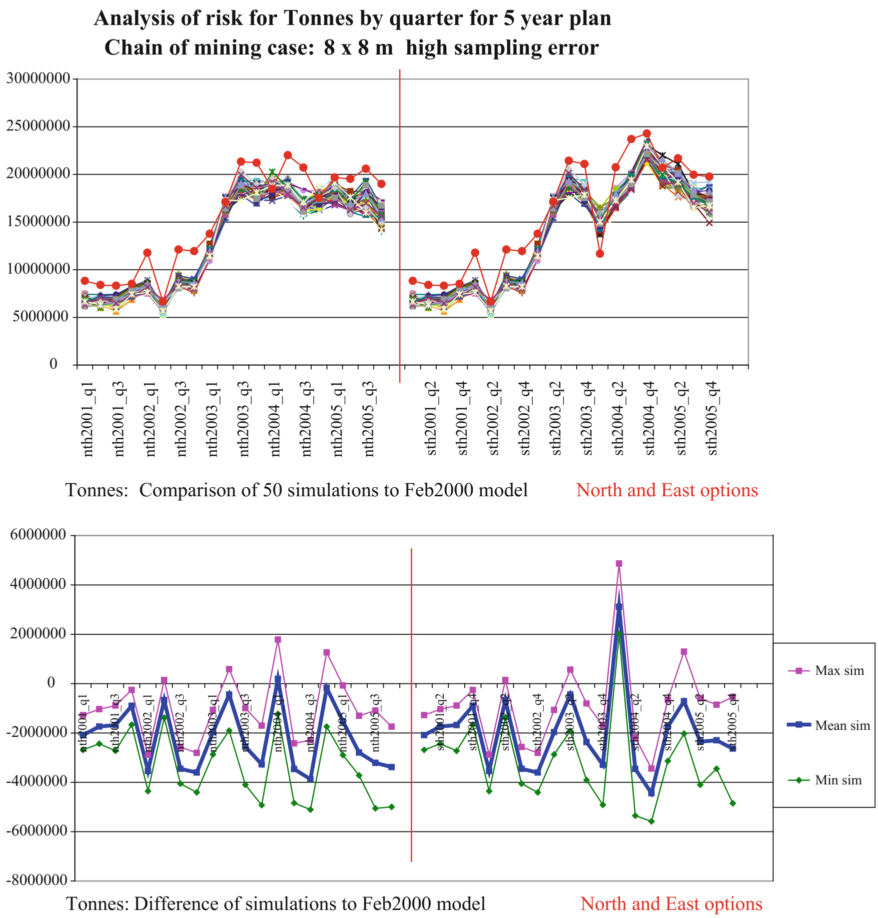

Fig. 9 Risk associated with tonnes in the five year plan by quarters

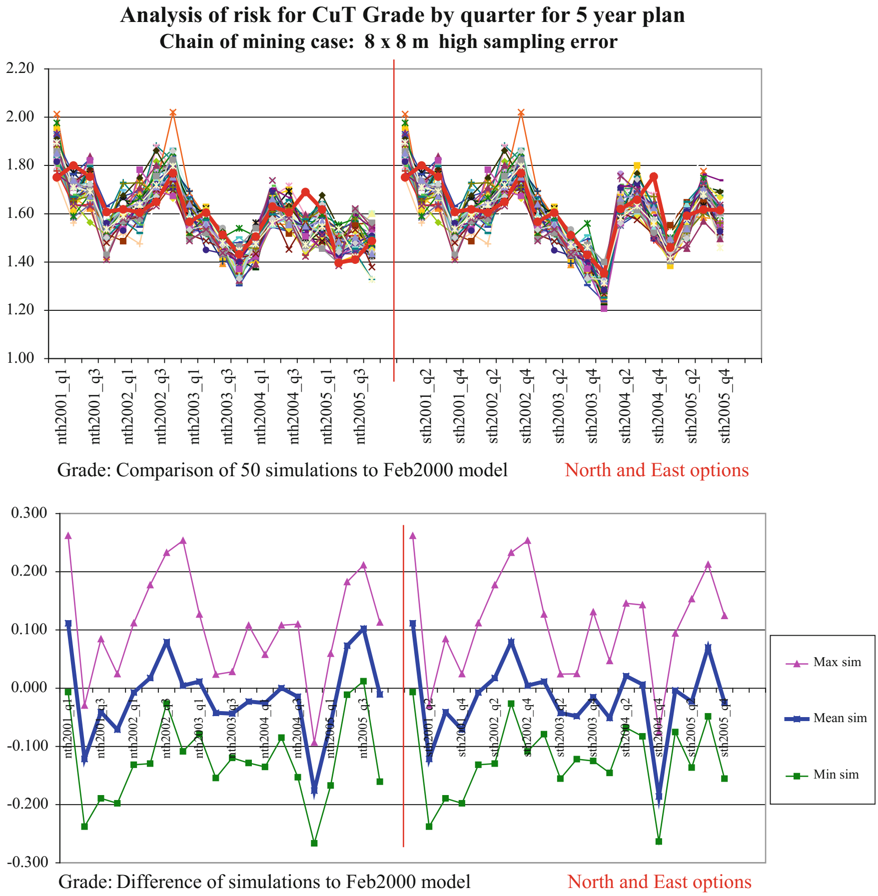

Fig. 10 Risk associated with grade in the five year plan by quarters

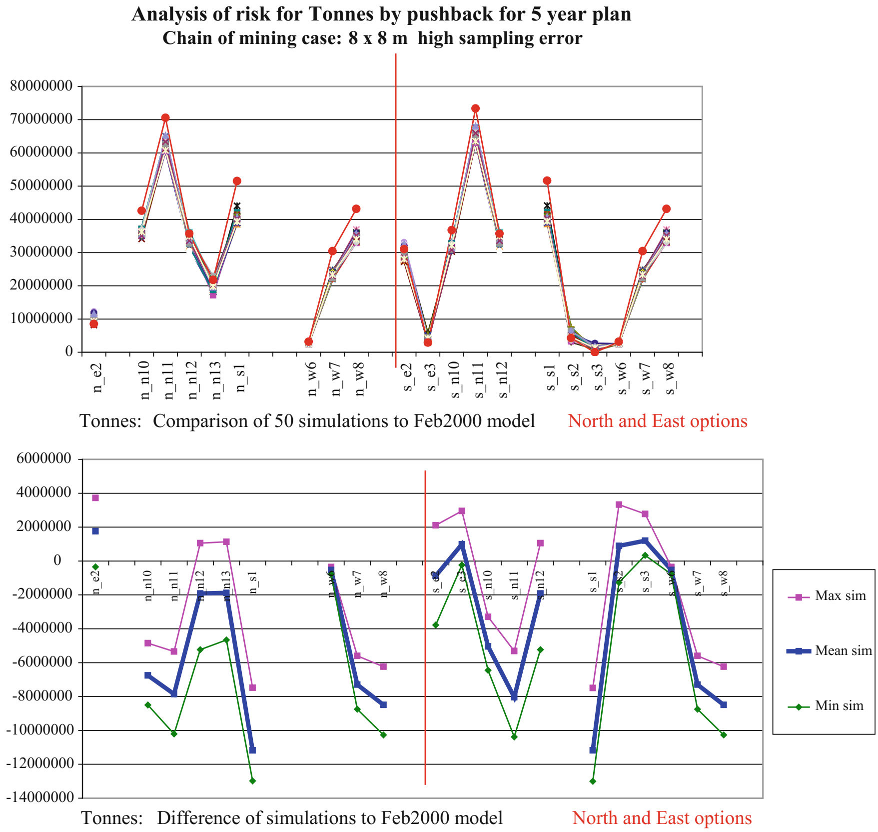

Fig. 11 Risk associated with tonnes in the five year plan by pushback

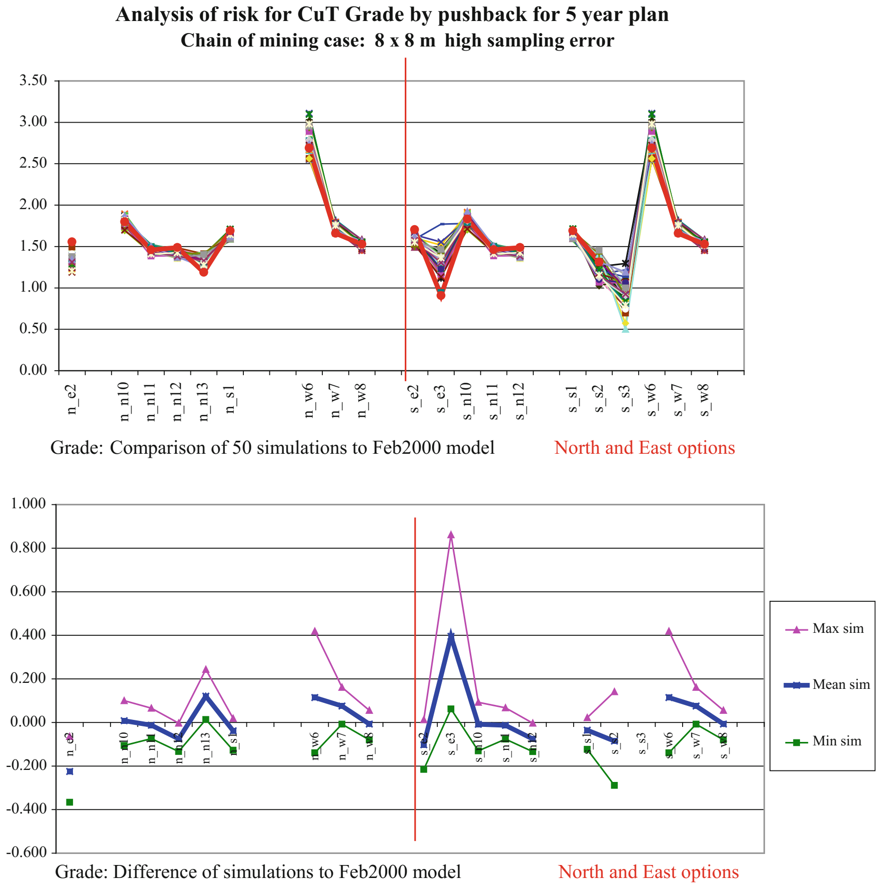

Fig. 12 Risk associated with grade in the five year plan by pushback

Conclusions

The five-year schedule options adequately fit with the in situ resource. However, the Chain of Mining case (8 × 8 m SMU, high error) selected to best emulate the production data indicates a significant expected shortfall in tonnes. What had not been evident until this study, and could only be demonstrated using the exhaustive data set provided by a conditional simulation study, is that there was considerable risk of a shortfall in tonnes. This was because the selectivity evident in the actual mining strategy differed significantly from that inherently assumed in the resource model. High quality grade control practices on site were effectively providing higher selectivity than that assumed in the resource model. This lead to a scenario of 'vanishing tonnes' (David 1977), a concept demonstrated in this study that is familiar to many large mines. This problem can be related to attempts to improve the head-grade to unrealistic targets applied on a short-term (sometimes daily) basis. Visual grade control and other decisions to remove small parcels of contaminating material in order to maintain a high mill head grade may lead to an artificially small effective mining selectivity that is not related to the SMU block size assumed in the resource modelling.

The quantification of risk using simulation of the Chain of Mining is a technique that can be used to identify a potential shortfall in tonnes or grade for a given mining scenario. Alternative plans can then be developed and tested before the shortfall impacts production. An approach such as the one demonstrated here for Escondida can determine if a plan is realistic and the predicted results will be obtained. Hence, the risk inherent in a given plan can be quantified. Testing alternate mining scenarios, operating practices and policies to determine if they will indeed deliver as intended, therefore, provides considerable advantages to both mine planners and operators.

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