New Approach to Recoverable Resource Modelling: The Multivariate Case at Olympic Dam

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Abstract Traditional estimation techniques significantly under-call the true monetary value of the resource on which mine plans and operations base their business. At Olympic Dam, this is worth billions of dollars. Realising this value requires mine planning engineers to be supplied with an accurate recoverable resource model that correctly estimates the tonnes and grade for a specified support and time scale, at the time of mining.

Models estimated using linear methods and wide-spaced drilling typically fail to accurately predict recoverable resources, mainly because of incorrectly accounting for the change of support and information effect. The unavoidable smoothing property of weighted averages is also a significant obstacle. These failures are more significant in underground mining scenarios where higher cut-offs (with respect to the average grades of mineralisation) are applied. This paper discusses a different approach to recoverable resource estimation based on conditional simulation methods.

The Olympic Dam deposit is one the world's largest polymetallic deposits. The resource estimation practices at Olympic Dam are comprised of a combination of linear and non-linear techniques to estimate 16 different grade variables critical to mine planning. Measured resources are supported by 20m-spaced underground drilling fans where Kriged estimates perform well in terms of mine to mill reconciliation. However, this not the case for resources classified as Indicated and Inferred. Until infill drilling is undertaken, the accurate estimation of tonnes and grade to the mill is not possible with the Kriged model. This has a significant impact on life-of-mine economic valuations and ore reserve estimates of Olympic Dam.

Conditional simulation has been used to generate a recoverable resource estimate from a single realisation. This conditional simulation model takes into account both the change of support and the information effect, without the undesired

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smoothing effect that classic methods introduce. This paper describes the significant challenges faced in applying this approach, including issues such as which realisation to choose; data conditioning in areas with little information; ensuring that the multivariate relationships among variables are respected at a block level; software and hardware challenges; and defining benchmarks for ensuring that the "correct" grade-tonnage curves are reproduced. These challenges have to be overcome while ensuring that the resulting estimate is a JORC-compliant, and is also acceptable under BHP Billiton's corporate governance standards.

Introduction

Olympic Dam is Australia's largest underground sub-level open stoping mine producing around 10 Mt of ore per annum. The Olympic Dam mine has been in production since 1988 using a standard mining method of mechanised sublevel longhole open stoping (SLOS), with cemented aggregate backfill. The processing plant is a fully integrated circuit that consists of autogenous grinding mills, flotation circuits to recover copper concentrate, and tailings leach circuits to recover uranium. The copper concentrate is treated in an onsite Direct-to-Blister-Furnace (DBF) smelter while an onsite refinery produces copper cathode and recovers gold and silver.

Olympic Dam is a very large iron oxide-hosted Cu-U-Au-Ag ore deposit. The deposit is hosted entirely within the Olympic Dam Breccia Complex (ODBC), and is unconformably overlain by approximately 300m of unmineralised, flat-lying, sedimentary rocks. The deposit was discovered in the late 1970's and the geology has been studied and described by numerous authors (Roberts & Hudson, 1983); (Ehrig, McPhie, & Kamenetsky, 2012). A key feature of the deposit is a central core of haematite–quartz breccia largely devoid of copper and uranium mineralisation. In general, the host-breccias are more haematite-rich towards the centre of the ODBC and more granitic at the margins. Including the sulphide minerals, there are more than 100 identified ore and gangue minerals. The most common minerals include haematite, quartz, sericite, feldspar, chlorite, barite, fluorite, siderite, pyrite, chalcopyrite, bornite and chalcocite. The three primary uranium minerals account for less than 0.1% of the total rock mass, and occur as uraninite, coffinite and brannerite.

The bulk of economic mineralisation is associated with sulphide-bearing haematite-rich breccias. The majority of copper mineralisation occurs as chalcopyrite, bornite and chalcocite, and dominantly manifests as binary pairings of chalcopyrite ± bornite, and bornite ± chalcocite. Uranium, gold, silver and copper minerals are all correlated to a statistically significant degree.

Why Produce a Recoverable Resource Model?

The business case for recoverable resource modelling is simple: the true monetary value of Olympic Dam is highly leveraged to grade. For example, depending on the specific mine plan, for every 10% increase in grade in the early part of the plan, there is a 25% increase in annual cash flow. Around two thirds of the life-of-mine is based on widely spaced drilling, and is therefore a smoothed and under-representative view of the grade that will be realised when close spaced drilling and high resolution estimation is undertaken. Modelling the correct distribution of grade is worth billions of dollars to the value of Olympic Dam.

In the past 40 or so years there have many attempts at producing effective recoverable resource models with varying degrees of success; some relevant discussions and case studies include (Journel & Huijbregts, Mining Geostatistics, 1978); (Journel & Kyriakidis, 2004); (Assibey-Bonsu & Krige, 1999); (Rossi & Parker, 1993); (Abzalov, 2006); (Krige & Assibey-Bonsu, 1999); (Rossi & Deutsch, 2014); (Roth & Deraisme, 2000).

In an environment of falling commodity prices, with a focus on reducing costs and improving financial metrics of cash flow, IRR, NPV and capital efficiency, an equally important consideration to costs is improving the revenue. The old adage, “grade is king” is never more true in this environment. For deposits that are relatively high grade, and where the spatial continuity of that grade is amenable to selective mining, increasing the grade for the same tonnage delivered to the mill is very effective in increasing the margin on each unit of metal produced. The mining cost per tonne of ore may increase but the cost per pound of copper can greatly decrease.

A common strategy at Olympic Dam has been to increase metal production by increasing process plant ore tonnage throughput. Unless there is latent capacity in the plant, there is a large capital requirement in order to accommodate the increase in tonnes. Alternatively, increasing metal throughput in the operation can be achieved by raising the grade of the ore feed from the mine, which is generally much less capital intensive since the plant is large and complex.

The Olympic Dam deposit is relatively high grade with contiguous zones of 2%-4% copper grade. This continuity of high grade gives the operation an opportunity in the planning and mining processes to increase the grade delivered to the processing plant. Relatively close 20m spaced lines of Measured Resource drilling is required to define these contiguous high grade ore shoots. The Olympic Dam Inferred Resource is defined by relatively wide-spaced drilling at 100-250m notional centres. Indicated Resource is defined by both wide-spaced surface and wide-spaced underground drilling at 70-100m centres. Comprehensive drill spacing studies (see later section) have back-tested the effect of re-sampling Measured Resource (20m drill spacing) at Inferred and Indicated drill spacings in the deposit. These studies have demonstrated that a traditional Ordinary Kriged (OK) linear estimate using this wide-spaced drilling information is neither globally accurate in terms of tonnes and grade, nor locally spatially accurate in representing the orientation of the high grade zones which are to be mined (Figure 1). This holds true for geological interpretations and models, estimated models, and simulated models, since these are a function of data spacing.

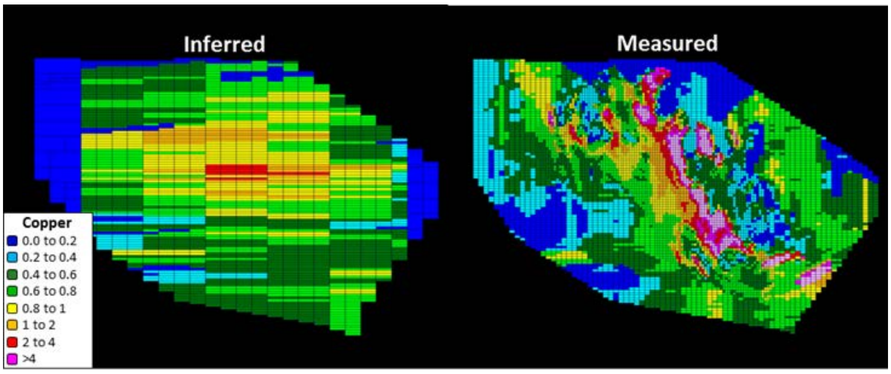

Figure 1: Representative cross-section through Olympic Dam showing differences in copper grade, modelled using Inferred (250m spaced) drill hole information, and Measured (20m spaced) drill hole information. Each model depicted above has a unique geological interpretation that is a function of the data spacing.

Over the longer term, how and when these higher grade ores are exploited can also have a direct impact on the life and the consequent NPV of the operation. Since the life-of-mine has approximately two thirds of the Resource at Indicated or Inferred status, there is a poor conversion of Resource to Reserve, which understates the overall value of the operation in the life-of-mine plans. In addition, experience at Olympic Dam and many other operations elsewhere has shown that for the same volume of material mined, an increase in grade is realised with later infill drilling. This is due to the high grade mineralisation controls that exist at a smaller scale, compounded by the well-documented support effect and the inherent smoothing of linear estimators such as Inverse-distance weighted and Kriging methods. The result is that estimates in areas with wide spaced information undercall the true tonnage and grade that are realised once close spaced drilling and high resolution estimation is undertaken.

In the authors’ experience, at Olympic Dam the most practical solution to overcoming this issue is to produce a recoverable resource model using a simulation technique. Conditional simulations which comprehensively validate against the drill hole data are the only technique that avoids smoothing by reproducing the original data variance (high granularity models), estimates the tonnes and grade at the time of mining for any drill spacing, and produces a better local spatial model that can be used for practical geological, mine planning and financial valuation purposes.

Combined with traditional OK estimates of Measured Resource, estimates of Inferred and Indicated Resource produced using conditional simulation are collectively referred to as the Recoverable Resource Model (RRM). This model is an enabler to several other mine planning value-adding initiatives which unlock the true value of the deposit. These initiatives are collectively referred to as the grade focus strategy.

The Grade Focus Strategy

The RRM is integral to the overall strategy to increase grade and value at Olympic Dam. This strategy is aimed at maximising the contribution of ore grade to the value proposition for the operation. Higher ore grades have a direct impact on the revenue stream, and are very effective in lowering the unit cost of metal production. This strategy is based on six key focus areas that all contribute to improving the value contribution of ore grade.

1) **Resource modelling**. By using conditional simulation to estimate grade in model areas supported by wide-spaced drilling, a higher grade from improved granularity can be realised in the mine planning process.
2) **Reserves**. By using a more sophisticated automated stope generation technique, a higher design grade can be realised through a more efficient capture of high grade resource.
3) **Resource utilisation**. By including all potential (pre-resource) mineralisation and Inferred Resource in the mine plan, the full possible value of the underground operation can be assessed, allowing a higher cut-off to be applied, and therefore a higher grade to be realised.
4) **Cut-off grade optimisation**. Historically the operation has been valued on a fixed cut-off grade. The future plan is to implement a variable cut-off strategy, where the cut-off varies between stopes and over time. This change in stope design practice will allow the optimisation process to add value by promoting grade in time, beyond the level achieved using a fixed cut-off.
5) **Rejection of sub-grade material from the ore stream**. Separate removal of below cut-off material and low grade development to the surface raises the average ore grade, and increases the proportion of high grade stope material in the ore stream.
6) **Stope sequencing and scheduling**. Higher value mine plans can be achieved by promoting higher grade stopes forward in the schedule, and deferring lower grade stopes in time.

Both the absolute and relative contribution of these areas to the value proposition will depend on the context of the specific mine plan that is being evaluated. The key point is that for the full value of the resource to be realised, all six areas are necessary. No modelling technique alone can realise the full value.

Fundamental Challenges

The development of a recoverable resource model for Olympic Dam has been a significant challenge. Some of these challenges are purely technical in nature, but there are also fundamental challenges that inhibit the acceptance of this modelling technique.

Ultimately, if recoverable resource models are not used to generate mine plans, then they are of little practical use. One of the critical factors to success is the support of mine planning engineers in understanding the value these models hold, and to use them for reserving. Without this, it is just another low value, esoteric exercise. To extract the maximum value from the model, the cultural inertia manifest as conservatism and fear of failure, must change, or the upside in grade will never be realised.

Gaining understanding and support from decision makers in the business has been one of the single greatest challenges. Concepts that are basic to geostatisticians and resource geologists (e.g., averaging, grade above cut-off, change of support and volume-variance) are obscure to decision makers, and are treated with suspicion and even derision. The lack of knowledge regarding these elementary concepts in the industry, its leaders, and some of the broader consultancy community to which these leaders defer, are real and significant barriers to the success of this work.

Technical Challenges

With regard to a deposit as large as Olympic Dam, there are several technical hurdles to overcome in attempting to produce a recoverable resource model using conditional simulation.

The model covers an area of 6 x 3km, and extends to a depth of 2km. It is comprised of 5 x 10 x 5m block support, from estimates using a number of techniques for different areas, elements and minerals in the deposit. All elements and minerals in areas classified as Measured Resource are estimated using Ordinary Kriging (OK). Within areas classified as Inferred and Indicated Resource, Cu, U_3O_8, Au, Ag, S and SG are estimated using conditional simulation. The copper mineralogy is stoichiometrically calculated from the simulated Cu and S estimates. All other elements and minerals are estimated using OK.

The dimensions of the deposit present the foremost challenge. At a 2.5m node spacing, a single model covering the entire deposit comprising of a minimum of 14 data variables would require ~1.5 billion nodes, and constitute a model file size in excess of 700GB. A single drill hole file used for this simulation would comprise of ~950,000 2.5m length samples. Working with these files is impractical, and there is no simulation software capable of handling such a large model file. To deal with this challenge, the deposit is split into 16 individual sub-models and corresponding drill hole files, based on gross geological differences and also the ability of the simulation algorithm and software to perform the task in a reasonable amount of time. Once these individual models are amalgamated into one model and regularised, there are no boundary artifacts evident in the combined model. The characteristics of these individual models are listed in Table 1.

Table 1: Some characteristics of Olympic Dam simulation models

Model Characteristics	**Group 1 Models**	**Group 2 Models**
No. of Models	9	7
Model Dimensions	~1 x 1 x 1km	~2 x 1 x 1km
Node Size	2.5 x 2.5 x 2.5m	2.5 x 2.5 x 2.5m
No. of Nodes	~64 million	~128 million
No. of Simulated Variables	6	6
No. of Total Variables	14	14
Model Run Time	~8 hours	~16 hours
Node Model File Size	~6.5GB	~12.4GB

Simulation is performed separately in the chalcopyrite ± bornite (220) domain, and the bornite ± chalcocite (230) domain, to allow the unique grade relationships observed in the drilling information (Figure 2) to be honoured. The domains are established by modelling the unique Cu to S ratios of these sulphides using a combination of deterministic modelling and probabilistic (Indicator Kriging) methods.

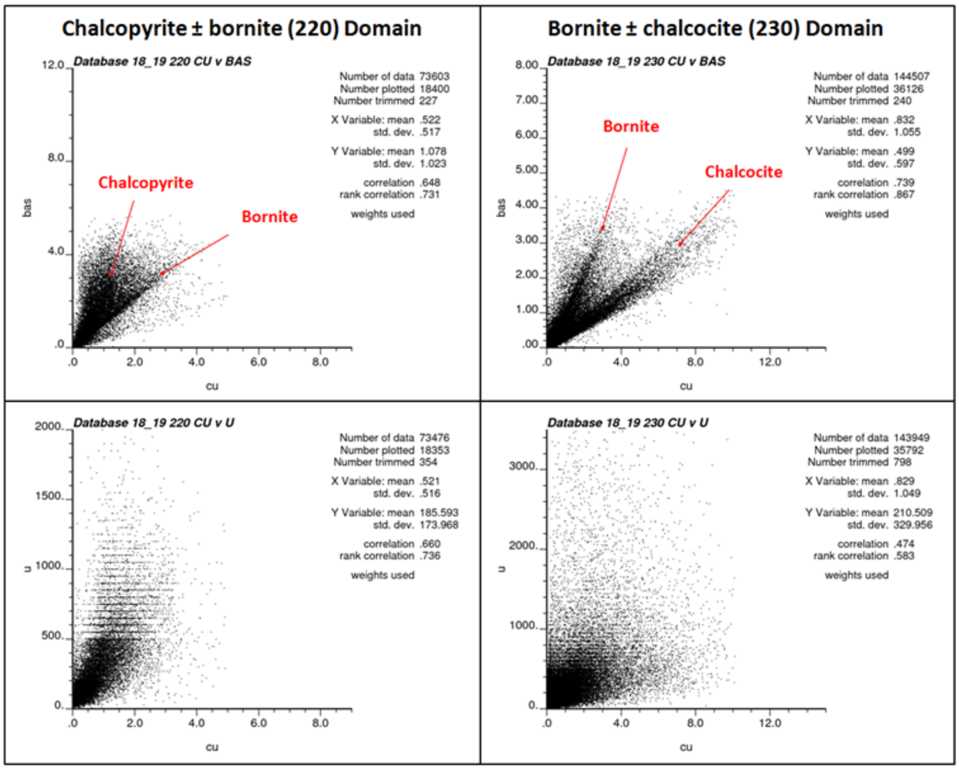

Figure 2: Scatter plots of Cu v S and Cu v U_3O_8 for the chalcopyrite ± bornite (220) domain, and the bornite ± chalcocite (230) domain for drilling information in Model 18_19 of Olympic Dam.

What Has Been Tested

A significant amount of work has been undertaken over the last few years to establish the foundations of the recoverable resource model at Olympic Dam. Significant improvements in deterministic modelling of the key sulphide domains, and work on previous simulation models of Olympic Dam, have also played a prominent role in determining the most efficient path forward. The key attributes required of techniques and software is the usability of models by mine planning, the speed and stability of the algorithm and software, the honouring of multivariate relationships between simulated variables, and the ability to integrate several models from several simultaneous sources.

In these authors' experiences, conditional simulation is the preferred technique for underground mine planning work rather than other techniques such as Uniform Conditioning (UC) and Multiple Indicator Kriging (MIK), because they suffer from the same smoothing effect evident in all forms of Kriging, and also produce models that are more suitable for input into open pit mine planning software.

Following extensive trials over several years, the resource team has settled on Sequential Gaussian Simulation (Isaaks, 1990) as the most appropriate algorithm to use. Stepwise conditional transformations (Leuangthong & Deutsch, 2003) are applied to account for the correlation between metals. Other algorithms, including co-simulation with Bayesian Updating (Journel A. G., 1988), (Rossi & Badenhorst, 2010) and Projection Pursuit Multivariate Transformation (Friedman & Tukey, 1974), (Barnett, Manchuk, & Deutsch, 2012) have been extensively trialled and rejected either because of poor reproducibility of input statistics, difficulty in replicating multivariate relationships observed in the drilling information, poor spatial match to input data, and the inability to deal with large datasets, or a combination of all of the above. SGS point simulation rather than Direct Block Simulation (DBS) is preferred since validation against the input data of DBS shows issues caused by the proportional effect present in the original data, which has been shown to introduce biases in the final output (Leuangthong, 2006).

Both commercially available and open source software have been used with varying degrees of success. Significant issues which were encountered included: software errors introduced by inconsistently incorporating GSLib-based routines (Deutsch & Journel, 1998); very slow operation with large datasets; stability issues and data corruption; or problems with integration of models from multiple users working simultaneously on different parts of the deposit. It is clear from almost a decade of work on this topic at Olympic Dam that it is unlikely that standard commercially available software packages can be used to produce recoverable resource estimates that meet the mine planning and the corporate governance requirements. Therefore a modified version of the GSLib programs has been adopted to complete the work.

In order to overcome some of the known issues with SGS, including edge effects and grade blow-outs between drill holes or at the edges of data, as well as to increase the program's functionality, the original GSLib FORTRAN code was modified in-house. One of the key enhancements made to the code was the implementation of multiple search passes with the ability to have different parameters for each pass. For this reason, the program has been named Dynamic Search SGS or DS-SGS. Other enhancements include the addition of domain control, not drawing from the global distribution, multiple coarse/fine grid redefined in terms of user input of x, y, z grid spacing, independent soft nodes and hard data search with assign to nodes selected, and minimum number of soft nodes selection with assign to nodes option.

Case Study

The aim of the case study was to examine the change in grade/tonnage information for an existing well-drilled 20m spaced Measured Resource area (here after referred to as “truth"), by estimating and simulating it using wider Indicated, and Inferred Resource drill spacings. The goal is to determine if the simulation parameters using the wide spaced drilling, yielded results that matched the 20m spaced Measured Resource truth, thus providing a mechanism to calibrate and validate simulation models in other areas of the deposit.

In order to do this, a conventional drill hole spacing-type approach was followed, but with a few differences. The starting point was to take a vast area of Measured Resource that has been drilled from underground on 20m spaced lines, and treat this as the “truth”. This area constitutes 1.3 billion tonnes of Mineral Resource and 300 Mt of Proved Ore Reserve, of which 170 Mt has been mined over the last 27 years (Figure 3).

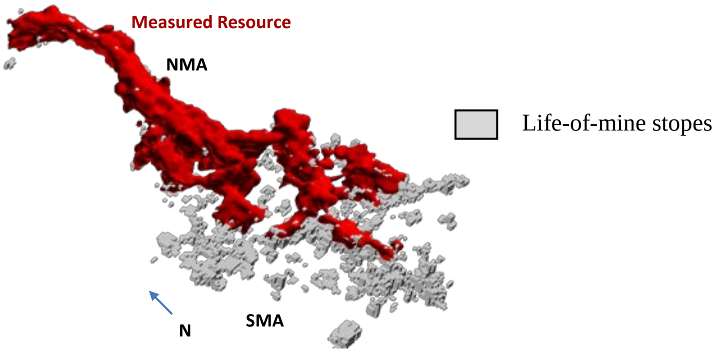

Figure 3: Location of Measured Resource in relation to the life-of-mine stope set. Note the extensive spatial coverage of Measured Resource across the deposit.

This represents approximately 30% of the expected ultimate underground reserve across the entire deposit, and is representative of the material that will be mined in future years. Mine to mill reconciliation results demonstrably show that over a 3 year period (~30 Mt), the estimated tonnes and grade of Measured Resource varies by less than 1% from that actually recovered. Thus, there is high confidence that the Measured Resource volume is a good yardstick by which to validate the simulation results.

One of the primary criteria for determining Resource classification is drill hole spacing, and for convenience will be used in this discussion. Table 2 shows the relative drill hole spacing applied at Olympic Dam for Inferred through to Measured Resource, and the relationship to the estimation support.

Table 2: Resource classification and drill spacing used at Olympic Dam.

Resource Classification	Drill hole Spacing	Model Block Size
Inferred Resource	250m	120x100x5m
Indicated Resource	100m	60x50x5m
Measured Resource	20m	5x10x5m

Comparing Raw Drill hole Data

A fixed volume of 20m spaced Measured Resource was originally drilled from the surface on 70-100m centres, and is equivalent to Indicated Resource spacing. These surface holes were re-sampled at 250m spaced centres to approximate the equivalent Inferred Resource drill spacing. This re-sampling was undertaken 25 times by randomly selecting holes at 250m centres in order to capture the range of possible outcomes from variations in the drilling grid. This process approximates a drilling program that starts at 250m spacing, and is then progressively infill drilled to 100m and 20m spacings. The outcome is a comparison of the Nearest Neighbour-declustered drill hole data statistics and grade-tonnage curves of the different grid spacings of 20m, 100m and the 25 iterations of the 250m spacing. The differences in results were alarming (Figure 4).

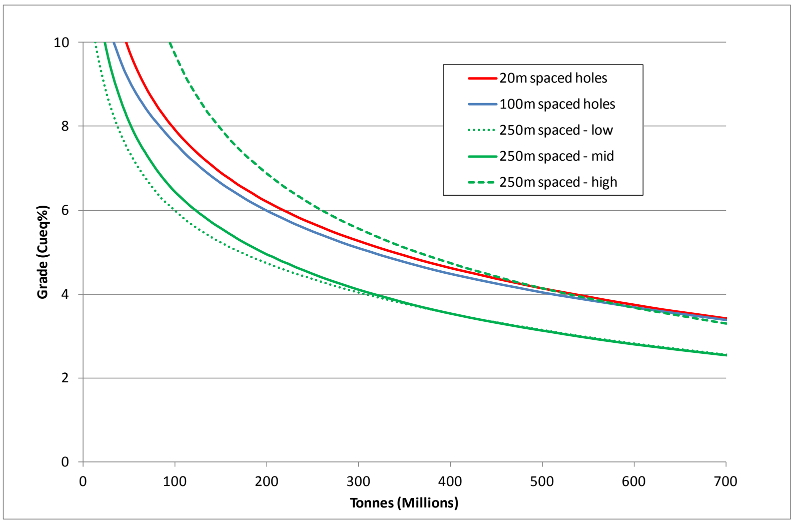

Figure 4: Declustered sample grade-tonnage curves within the Measured Resource volume. The differences in information for the 100m dataset and 250m re-sampled datasets are clearly demonstrated. Cueq = Cu + (U_3O_8*2.44) + (Au*0.881) + (Ag*0.0048) – (S* 0.191).

There is considerable difference among the twenty five 250m iterations with 23 (92%) of them under-calling the actual tonnes and grade by a considerable margin, whereas the 100m spaced drilling dataset is much closer to the 20m spaced dataset. In classical geostatistics, this is termed the Information Effect, or more precisely, in this case, the Misinformation Effect.

Comparing the 100m-based and 25x250m-based Model Estimates

Each of the 250m drilling datasets had its own geological model and domains, and was used to create 25 separate resource models that were estimated using Ordinary Kriging into block sizes of 120x100x5m. The same process was applied using the 100m spaced dataset to a model with unique geological and domain characteristics, and a 60x50x5m block size. The resource grade tonnage results mirrored the differences observed in the drilling data noted previously. The 26 estimated models (25 Inferred and 1 Indicated) were then converted to Reserves by the mine planning engineers running each through an automated and semi-automated stope design process.

The results from the Reserve grade-tonnage curves mirrored that of the resource models, and also the underlying drill hole data. That is, if the drill hole dataset was the lowest of the group on the grade-tonnage curve, then the corresponding resource and reserve models were also the lowest (Figure 5).

A Sequential Gaussian Simulation was then developed using 3 of the 25 Inferred datasets by choosing a low, mid and high iteration of drill hole data. An additional simulation model was also generated using the single 100m spaced Indicated dataset. The results mirrored those of the drill holes, and resource and reserve models discussed earlier. The results are very clear; the underlying data exerts the strongest control on whether or not the 20m spaced Measured Resource grade-tonnage result can be achieved from wide-spaced Inferred or Indicated Resource datasets. The conclusion is that all resource and reserve models, be they estimated or simulated, are strongly anchored to the starting drill hole data. Locally, different mine areas typically behaved differently from iteration to iteration. Most of the 25 Inferred Resource datasets were low with respect to the 20m spaced Measured Resource "truth", but a few were higher. This is a random feature, and is attributed to chance interactions with geological influences.

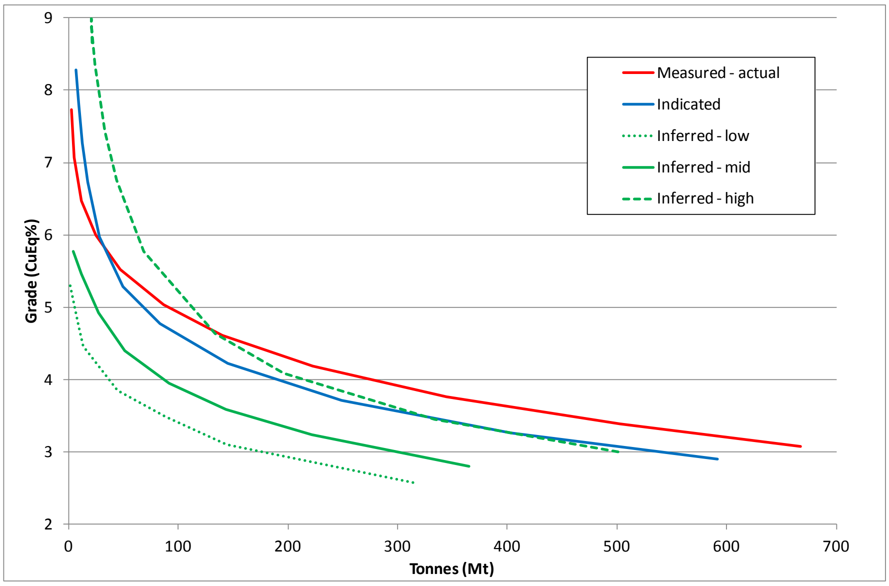

Figure 5: Comparison between Ore Reserve grade-tonnage curves using Measured Resource, and re-sampled Indicated and Inferred Resource models. Cueq = Cu + (U_3O_8*2.44) + (Au*0.881) + (Ag*0.0048) – (S* 0.191).

Observations & Discussion

A critical observation is that there is a fundamental change to the drill hole information from iteration to iteration for the same spacing, as well as when the grid spacing decreases. The proportions of grades change above a cut-off and the overall volume of mineralised material increases. This happens in 92% of the cases described; however there were a few 250m spaced iterations (8%) where the proportion and grade of drill holes were higher than the 20m spaced Measured Resource "truth". Locally the pattern of uplift or downgrade can differ significantly from that observed globally.

These differences are due to imperfect information (including sampling and estimation error), non-representativeness of data at a certain spacing, and chance interactions of drill holes with complex geology and geometry. There is natural variation in the orebody which means certain drill spacing and orientation with respect to orebody geometry are not adequate to fully sample the real distribution and proportions of grades. This can lead to an over-representation of low values and under-representation of high values, and vice-versa, which results in vast differences in reserve stope shapes (Figure 6). The Misinformation Effect is used in this case as a collective term to describe all of the aforementioned errors and effects, which is more encompassing than the traditionally used Information Effect. Whilst there is a relationship between the two, the term Misinformation has been chosen to avoid pedanticism and confusion.

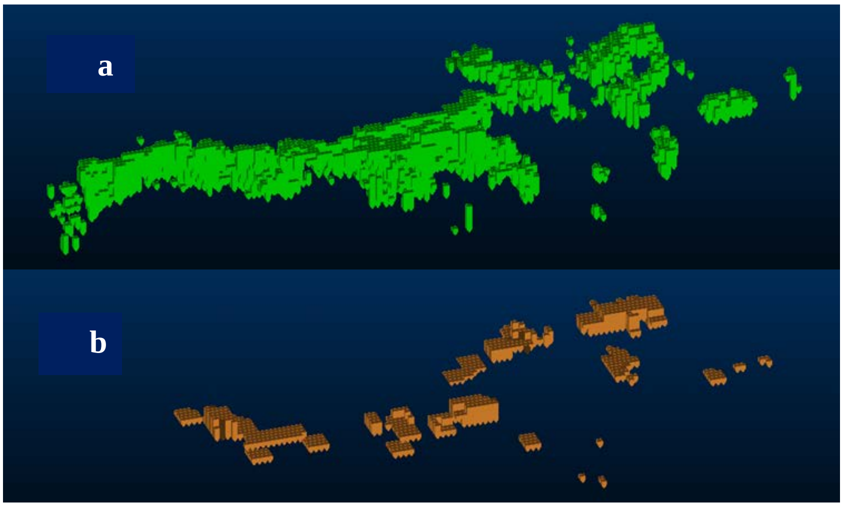

Figure 6: Comparison between reserve stopes in the Measured Resource volume at the same cut-off, using (a) Measured Resource model and (b) one of the 25 re-sampled Inferred Resource models. Note how poorly the Resource estimate based on Inferred Resource drill spacing estimates the mineable tonnes for the same mining area.

At Olympic Dam, the Misinformation Effect in volumes informed by wide-spaced data leads to underestimation of the actual tonnes and grades.

Regardless of the drill spacing, the best that can be done by the practitioner is to honour the available drill hole data. This approach will not capture the range of uncertainty, and therefore a different strategy is required to account for the Misinformation Effect. The Olympic Dam Mine Planning department will employ the use of modifying factors based on reconciliation to account for the global upside from the Misinformation Effect, allowing for local differences that may result in downside.

Which Realisation to Choose?

Conditional simulation is commonly used for quantifying resource uncertainty. Typically this approach involves generating numerous realisations, and developing probabilities and confidence intervals from these. The multiple realisations are interpreted as values of the conditional cumulative distribution function (ccdf) of each node:

$$Prob^{*}\left\{Z(x) \leq z_c \mid (n)\right\} = F\left(x, z \mid (n)\right) \tag{1}$$

where “Prob*” represents the estimated probability at location $\underline{x}$; Z($\underline{x}$) represents the random variable at location $\underline{x}$; z_c represents an arbitrary cutoff; (n) represents the conditioning data used to simulate node at location $\underline{x}$; and F represents the conditional distribution function.

Unfortunately, when conditional simulation is used for recoverable resource modelling, this same “many realisations” mindset is mistakenly also applied, leading to questions about the number of realisations generated during simulation and the decision processes used to select a single realisation for further processing. What most practitioners do not realise, and most theoreticians ignore, is that the change of support variance is much more significant than the variance of the conditional distribution provided by simulation. A change in mindset is required to accept that conditional simulation can be a valuable recoverable resource technique.

As the overall volume of the simulation increases, the global difference between the realisations becomes progressively smaller. For a large model area of ~1.6 billion tonnes of resource and ~270 Mt of reserve, the difference between realisations is ~1%. Over the entire deposit of >10 billion tonnes, the difference is <0.5% whereas the difference between small blocks and big blocks is >20% for this same area.

When examining simulation realisations at the small block scale, realisations can exhibit significant local variation, leading to the erroneous conclusion that selecting a meaningful single realisation for further work is difficult or problematic. This erroneous conclusion is reached because of a failure to appreciate that during recoverable resource modelling of large areas, the difference in the change of support is an order of magnitude greater than the spread of realisations. In a sense, the realisations converge to approximate the same solution when considering large volumes. This change in variance is governed by the volume-variance relationship, which can be illustrated by examining the change in mean grade above a cut-off for varying block sizes. The tabulation below shows this effect with 100 Cu realisations for three different levels of support for a ~270 Mt parcel of material that is expected to convert to Ore Reserves from the North Mine Area of Olympic Dam. The volume is a mixture of drill spacings that support Measured, Indicated and Inferred Resource.

The results clearly indicate that as the block size increases, the average grade above the cut-off substantially decreases for the same tonnage of material. This decrease in relative terms, which comes about solely from the change of support, is an order of magnitude greater than the variability between individual simulation realisations at the small block scale (Figure 7).

Table 3: Change in average Cu reserve grade above a 1.5% Cu cut-off for 100 simulation realisations at varying support size.

				Relative Change in Ave Grade		
Block Size (m)	**5x10x5**	**60x50x5**	**120x100x5**	**120x100x5 to 5x10x5**	**60x50x5 to 5x10x5**	**120x100x5 to 60x50x5**
Drill Spacing	20m	70-100m	100-250m			
Average Grade	2.65%	1.86%	1.66%	60%	43%	12%
Spread of realisations	~1%	~1%	~1%			

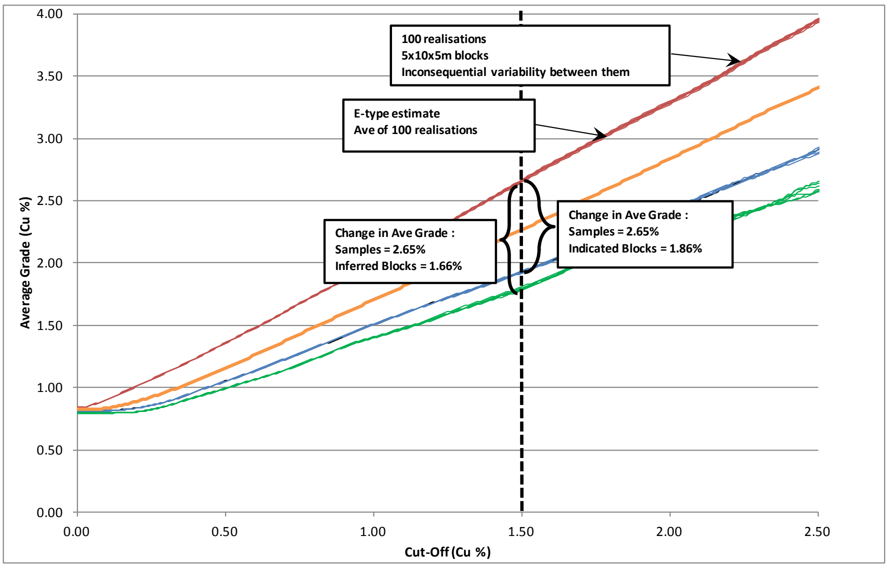

Figure 7: Grade curve for 100 realisations of 5x10x5m (red), 60x50x5m (blue) and 120x100x5m (green) Resource blocks showing the change in average grade for different support. The E-type curve (orange) is the average of 100 realisations at the 5x10x5m support.

Thus, for recoverable resource modelling of this large deposit, the number of realisations in a simulation is not critical. A single realisation, chosen at random from a handful is more than adequate to deal with the change of support problem. However, to emphasise the difference between the realisations at the local scale, a number of simulations models should be evaluated by the mine planning engineers. Moreover, as the size and area of the simulation increases there is no global low, mid or high realisation; this is a misnomer. One realisation that is lowest in one particular area may be the highest in another. Globally, there is no difference between realisations, so any realisation could be used to develop a mine plan as well as the basis for Mineral Resource declaration purposes.

It should be noted that this local difference between simulation realisations does not diminish the usefulness or applicability of the technique. Furthermore, the OK version of the model is just as incorrect locally; it is just that it is almost always overlooked. Inferred Resource is inferred because there is significant local uncertainty, regardless of the modelling technique used. An estimation method *senso-stricto* does not significantly alter this fact. The only way to reduce the local uncertainty is to gather more information through drilling.

The E-type estimate is often suggested as a suitable estimate for recoverable resources. The E-type estimate of 5x10x5 blocks is very smooth and negates the change of support correction that is sought (see Figure 7). The variance of the E-type under calls the actual variance through the mere averaging process and thus it is inappropriate as a representation of the true grade-tonnage relationship.

The purpose of the recoverable resource modelling work is to produce a block model suitable for life-of-mine underground mine planning and financial valuation, public declaration of Resource and Reserves, and drill targeting by mine geology. The absolute accuracy of the spatial location of stopes in the RRM is not as important for underground mine planning purposes as the representation of the spatial geometry of ore and the grade architecture.

Conclusions and Recommendations

There is a strong and compelling business case for focussing on grade improvements at the Olympic Dam operation. Two thirds of the life-of-mine reserves are based on wide-spaced drilling, which under-calls the grade that will be realised when close spaced drilling and high resolution estimation is undertaken. Modelling the expected grade is worth billions of dollars to the operation.

Conditional simulations that exhaustively validate, both visually and statistically, against the drill hole data is the only technique that:

- avoids smoothing by reproducing the original data variance (high granularity models);
- estimates the tonnes and grade at the time of mining for any drill spacing;
- produces a better local spatial model that can be used for practical geological, mine planning and financial valuation purposes.

The recoverable resource model is the main element that underpins a 6 point strategy aimed at increasing the grade of the ore feed from the mine. The strategy includes improvements to mine planning and mining practices which are all required to realise the full impact of value improvement.

The development of a recoverable resource model has not been without challenges. The most significant is communicating the elementary resource concepts and principles to decision makers whom lack the specialised technical skills required to fully appreciate the importance of recoverable resource modelling. This is possibly the single largest inhibitor to a successful recoverable resource model.

Technical challenges for the Olympic Dam recoverable resource model are mostly about the size of the orebody and the inability of available software to address the large file sizes required. The only practical solution is to modify the existing GSLib SGS routine, and create a fit-for-purpose algorithm. Reproduction of the correlations among multiple metals pushes the limits of application of the Stepwise Conditioning transform method employed.

The application of a single realisation for recoverable resources is outside the usual scope for conditional simulation, see for example (Goovaerts, 1997); (Dimitrakopoulos, 1999); (Krige, Assibey-Bonsu, & Tolmay, 2004); (Van Brunt & Rossi, 1999). It is therefore important to realise that in this case a single realisation provides the additional value that the operation requires, and why the usual objections to using a single realisation are not applicable.

The drill hole spacing case study demonstrably shows the impact of the Misinformation Effect; a term coined to describe all the unknowns in a resource estimate. All estimates, regardless of whether they are performed using traditional linear or non-linear techniques, are highly leveraged to the starting dataset. No amount of “alternate modelling”, multiple simulation realisations, or range analysis can fully describe the uncertainty inherent in the starting dataset.

Regardless of the drilling dataset, the best that can be done by the practitioner is to honour the available information. This approach will not capture the range of uncertainty, and thus the Olympic Dam Mine Planning department will employ the use of modifying factors to account for the Misinformation Effect.

The most common applications of conditional simulation require many realisations to be evaluated. This is not the case for change of support modelling at Olympic Dam, and perhaps on many other large deposits, since the global differences between realisations are an order of magnitude less than the difference between change of support models. However, there can be significant local differences between realisations and to quantify this impact; a handful of realisations should be given to mine planning for evaluation.

The internal company governance requirements have made it harder to produce a recoverable resource model as the basis for a Mineral Resource declaration. It is expected that the non-technical hurdles that these requirements bring about may be overcome as management is further educated in the value of the using a conditional simulation for resource estimation.

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