Integration of assay and cross-hole
tomographic data in orebody modelling: joint
geostatistical simulation and application at
Mount Isa mine, Australia
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Integration of assay and cross-hole tomographic data in orebody modelling: joint geostatistical simulation and application at Mount Isa mine, Queensland

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Synopsis
An extended conditional indicator simulation method is described that can be used to integrate cross-hole tomographic data with traditional diamond drill-hole assay data. The non-parametric, stochastic simulation algorithm allows modelling based on the ‘hard’ assay data while ‘soft’ tomographic data are used where appropriate, having regard to their quality or accuracy and compatibility with the assay data. The technique is demonstrated through an application at Mount Isa copper mine, Queensland, Australia, where it was used to integrate cross-hole conductivity data obtained by the radio imaging method into orebody modelling on the basis of Cu assay data. Modelling based on the direct integration of diverse data is a promising and powerful tool for advanced orebody modelling.

Traditional orebody modelling is based on borehole assay data. Recent developments in geophysical imaging in metaliferous mining environments—in particular, cross-hole tomography—have generated a substantial amount of information that can be incorporated into the orebody modelling process. However, the ‘fuzzy’ nature of the cross-hole tomographic data requires technologies that can integrate diverse data.

This issue of data integration or fusion is not unique to orebody modelling and mining. The integration of diverse information, such as borehole and geophysical data or, more generally, integrating ‘hard’ and ‘soft’ spatial data, is well known in the petroleum industry. Despite developments in other fields, however, orebody modelling based on diverse data integration is in its early stages as a consequence of the quite recent development of in-mine geophysical methods as well as related problems unique to the hard rock mining environment.

Geostatistical simulations are increasingly used for orebody modelling and mine planning in both open-pit and underground mining ventures. Conditional simulation techniques provide the means to quantify and assess the geological uncertainty of orebody attributes as well as to link this uncertainty to engineering processes, profitability criteria and decision-making.

The present contribution describes an extended conditional indicator simulation method that has been developed for the integration of cross-hole tomographic and borehole assay data. An account of the application of the method at Mount Isa Mines demonstrates the use of the algorithm in the integration of cross-hole conductivity data acquired by the radio imaging method (RIM) with copper assay data for diamond drill-hole (DDH) samples.

Geostatistical simulation algorithm
Geostatistical simulation is a Monte Carlo-type simulation used to generate equally probable models of orebody attributes, such as grades. An extended sequential simulation algorithm that can be used to generate equally probable models of orebody attributes while integrating diverse data is presented below.

Sequential simulation
Consider a stationary and ergodic random function (RF), $Z(x)$, with a multivariate probability density function $f(x_1, x_2, ..., x_M, z_1, ..., z_M)$. $Z(x)$ could, in geostatistical terminology, represent the grade of a mineral deposit. Sequential simulation is based on the decomposition of the multivariate probability density function (pdf) of the RF $Z(x)$ into a product of univariate conditional distributions:

$$f(x_1, ..., x_M, z_1, ..., z_M) = f(x_1; z_1) \cdot f(x_2; z_2|Z(x_1) = z_1) \cdot ... \cdot f(x_M; z_M|Z(x_1, ..., x_{M-1}) = z_a, a = 1, ..., M-1)$$

where $M$ is the number of locations within the orebody and $z_a$ is a value at location $x_a (a = 1, ..., M - 1)$. The decomposition in equation 1 shows that when generating a realization of $Z(x)$ the first value is drawn from the marginal distribution $f(x_1; z_1)$. The second value drawn comes from the distribution $f(x_2; z_2|Z(x_1) = z_1)$, which is conditional to the value $x_1$ drawn from $f(x_1; z_1)$, and so on.

If all the univariate conditional distribution functions (cdf) in equation 1 are known, $Z(x)$ can be simulated by sequentially drawing from each of the $M$ conditional distributions. In practice an initial data-set, $\{z(x_a), a = 1, ..., N < M\}$, is available. The sequential drawing begins at the $N + 1$ step and the first value comes from the univariate conditional distribution $f(x_{N+1}; z_{N+1}|Z(x_1, ..., x_N) = z_a, a = 1, ..., N)$. Subsequently, the remaining pdf are estimated one by one, each time conditional to the previously drawn values. The simulation and drawings stop when the last conditional distribution is estimated and a value is picked from it.

Joint sequential indicator simulation for hard and soft data
Sequential indicator simulation (SIS) is sequential simulation implementation based on the estimation of univariate conditional distributions by use of an indicator kriging approach, as suggested by Journel and Alabert. The method can be extended to account for both ‘soft’ and ‘hard’ data. Frequently, additional deposit attributes may be available, such as secondary data-sets that can be integrated into the modelling process. For example, in a copper deposit a primary, or ‘hard’, data-set may represent copper drill-hole assays, whereas a secondary, or ‘soft’, data-set may consist of
conductivity values derived from RIM tomographic surveys in the mine.

Consider a RF \( Z(x) \), as described previously, represented discretely by \( K \) mutually exclusive classes, \( I(x; z_k) \), using a series of \( k \) cutoffs. The SIS objective is the simulation of the spatial distribution of the \( K \) class indicators. A secondary data-set, \( \{ y(x); a = 1, \ldots, M \} \), may be integrated into the estimation of the local cumulative cdf (ccdf) of the primary attribute, \( Y(x) \), by first transforming it to an indicator RF, \( Y(x; z_k) \), similarly to the indicator transform, \( I(x; z_k) \), of \( Z(x) \). The related algorithm is as follows.

(i) Define a random path to be followed by visiting each location \( x \) (or grid node) to be simulated. There are \( L \) grid nodes to be visited.

(ii) Estimate at the first location—say, \( x_1 \)—the whole ccdf of \( Z(x) \) using indicator kriging and for \( K \) classes \( z_k \), \( k = 1, \ldots, K \)

\[
F(x_1; z(N))^* = \text{Prob}^*\{Z(x_1) > z(N)\} \\
= \left[ I(x_1; z_k) \right] 2 \sum_{a=1}^{N} c_{a} F(x_1; z_k) + \sum_{b=1}^{M} c_{b} Y(x_1; z_k) 
\]  

(2a)

(iii) Draw a value from the ccdf at the first location \( x_1 \) and add the corresponding results in the data-set. The new data-set is now \( \{ x; a = 1, \ldots, N + 1 \} \).

(iv) Move to the second location in the path—say, \( x_2 \)—and estimate the local ccdf of the \( K \) classes

\[
F(x_2; z(N + 1))^* = \text{Prob}^*\{Z(x_2) > z(N + 1)\} \\
= \left[ I(x_2; z_k) \right] 2 \sum_{a=1}^{N+1} c_{a} F(x_2; z_k) + \sum_{b=1}^{M} c_{b} Y(x_2; z_k) 
\]  

(2b)

(v) Draw a value from the estimated ccdf, add the value in the data-set, move to \( x_3 \) and repeat the process until a value is drawn from the last ccdf at location \( x_2 \).

The weights \( c_{a} \) are weights for the hard and soft data, respectively. The data weights required for these are derived from the solution of the following system of equations, termed indicator co-kriging:

\[
\sum_{a=1}^{N} c_{a} C_f(x_a, x_a') + \sum_{b=1}^{M} c_{b} C_f(y_a, y_a') + \mu_1 = 0
\]

\[
\sum_{a=1}^{N} c_{a} C_f(x_a, x_a') + \sum_{b=1}^{M} c_{b} C_f(y_a, y_a') + \mu_2 = 0
\]

\[
\sum_{a=1}^{N} c_{a} C_f(y_a, y_a') = 1, \quad \sum_{a=1}^{N} c_{a} = 0
\]

(3)

where \( C_f(h; z_k) \), \( C_f(h; z_k) \) and \( C_f(h; z_k) \) are, respectively, the indicator covariances for cutoff \( z_k \) of the primary data-set and of the secondary data-set and their cross-covariance.

To reduce the need for inference and modelling of each of these covariances (equation 3) a Makrov–Bayes formalism may be used, as suggested by Zhu, to allow the calculation of \( C_f(h; z_k) \) and \( C_f(h; z_k) \) directly from \( C_f(h; z_k) \):

\[
C_f(h; z_k) = B(z_k)C_f(h; z_k)
\]

and

\[
C_f(h; z_k) = |B(z_k)|C_f(h; z_k) \quad \text{for } h > 0
\]

\[
C_f(h; z_k) = |B(z_k)|C_f(h; z_k) \quad \text{for } h = 0
\]

(4)

where \( B(z_k) \) is generated from calibration of the primary and secondary data. \( B(z) \) is an accuracy index, equal to one when the secondary data are fully equivalent to the primary.

Case study at Mount Isa copper mine

The simulation technique outlined above was used at Mount Isa to simulate copper grades in a cross-hole region employing conductivity data derived from a RIM tomographic survey in part of the orebody as well as DDH Cu assay data.

General geology and RIM tomography

Mount Isa Mines exploits complex copper and silver–lead–zinc orebodies in northwestern Queensland. The orebodies occur within the upper part of the Urquhart Shale, a dolomitoc, calcareous and pyritic unit within the Western Fold Belt of the Proterozoic Mount Isa Inlier. The formation forms part of the Proterozoic siltstone shale sequence known as the Mount Isa Group. At Mount Isa 35 orebodies can be mined individually. The mineralization is grouped into either strata-bound silver–lead–zinc, which occurs as massive sulphide beds, or discordant copper—principally chalcopyrite occurring as irregular bodies surrounded by a silica doiminate alteration halo.

The RIM tomographic survey described by Stolarczyk is a geophysical imaging method that can be used to delineate conductive mineralization, such as the copper orebodies at Mount Isa. The method uses the attenuation property of the radio-frequency electromagnetic waves between a pair of drill-holes to measure the conductivity of the cross-hole area. The electromagnetic conductivity is then expected to reflect the copper content of the mineralization. The method was used at Mount Isa Copper mine in 1995 and at a site located at Level 19, almost 1 km below surface. The orebody at that level is predominantly chalcopyrite with associated pyrite and pyrrhotite. Fig. 1 shows the location of cross-holes 951106 and 951107 used for the RIM survey. Fig. 2 shows the resulting cross-hole RIM conductivity tomogram. In addition, Fig. 2 shows the assay data at the drill-hole locations. Details of the RIM survey and conductivity tomogram at Mount Isa have been given by Fullagar et al. and Zhou et al. and are beyond the scope of the present work.

Fig. 2 suggests that the overall correspondence between the RIM conductivity and Cu assay data is reasonable. However, it is also evident in Fig. 2 that the local correspondence of conductivity with Cu grades at various depths along the drill-holes varies from excellent to very poor. Although the RIM tomogram provides valuable information, orebody modelling requires much more accurate copper grade data. Thus, there is a need to develop methods that can use the ‘soft’ RIM data jointly with the ‘hard’ geochemical Cu assay data, when and where appropriate, to ensure that full use is made of all available pertinent information and so maximize the reliability of the orebody models produced. The availability of secondary information from the RIM survey generates
Fig. 1  Schematic geological section and drill-holes (951106 and 951107) for RIM conductivity tomogram at Mount Isa mine.

Fig. 2  Mount Isa RIM tomogram, cross-holes and their DDH copper grades. Note that conductivity and Cu grades have different units and range of values; squares represent Cu grades of composites along drill-holes.
a new technical challenge. The technique described in the previous section addresses this by accommodating the integration of secondary data whose correlation with the primary data changes for various ranges of values as well as spatially. This integration is obtained by applying the general indicator simulation approach (including the use of indicator cross-covariances) and calibration through the $B$ coefficients in equation 4.

**Data characteristics and statistics**

The characteristics of the Cu assays and the ‘co-located’ conductivity data are summarized in Figs. 3 and 4, respectively.

![Histogram of diamond drill-hole-derived per cent Cu assays](image1)

**Fig. 3** Histogram of diamond drill-hole-derived per cent Cu assays

![Histogram of co-located conductivity data, S/m, from RIM survey](image2)

**Fig. 4** Histogram of co-located conductivity data, S/m, from RIM survey

The data statistics are based on 1-m composites available at the cross-holes. The correlation of the co-located Cu assay and conductivity data is presented in Fig. 5. The figure shows that, generally, the correlation of the co-located data is relatively weak and the correlation of the data for various Cu grade cases and conductivity varies.

The implementation of the extended SIS technique is based on the selection of a series of Cu grade cutoffs. Six were used here: 0.5, 1.0, 1.7, 2.1 and 5.2% Cu. The grade 1.0% Cu corresponds to the median grade of the drill-holes available at the location of the RIM tomogram. The selection of cutoffs is combined with cutoffs on the secondary conductivity data such that the combination maximizes the correlations for the two series. The implementation of equation 3 is based on the ‘mosaic’ indicator kriging model. Accordingly, the indicator correlogram (or covariance) at the median cutoff is used. Use of this model is sufficient to demonstrate the technique, although further work on site could enhance future implementation. The median indicator correlogram used here is generated from

$$
\rho_f(h; z) = \rho_c(h) = \frac{1 - \gamma_{R}(h)}{\sigma_R^2} \quad \text{with} \quad F(z) = 0.50 \quad (5)
$$

where $\gamma_{R}(h)$ is the global relative variogram of the corresponding ore zone, $\sigma_R^2$ is a relative variance and $\rho_c(h)$ is the correlogram of the actual grades. The variogram of the orebody zone to which the data correspond is given in Table 1 and is used in equation 5.

<table>
<thead>
<tr>
<th>Strike</th>
<th>Dip</th>
<th>Pitch</th>
<th>Variogram type</th>
<th>Sill</th>
<th>Parallel Pitch</th>
<th>Perpendicular Pitch</th>
<th>Plane</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>25</td>
<td>0</td>
<td>Nugget</td>
<td>0.27</td>
<td>0.35</td>
<td>1.15</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Spherical</td>
<td>0.35</td>
<td>115</td>
<td>90</td>
<td>45</td>
</tr>
</tbody>
</table>

The application of the simulation algorithm requires the selection of cutoffs for the secondary data. The selected cutoffs for conductivity were 1.50, 2.00, 2.25, 2.50, 3.00 and 3.5 mV. The corresponding calibration coefficients, $B(z)$, were calculated as described by Deutsch and Journel and are 0.13, 0.21, 0.09, 0.11 and 0.08 for Cu cutoffs of 0.25, 0.50, 1.0, 2.1 and 5.2%, respectively. Note that the generally low $B(z)$ coefficients reflect the relatively low correlation of per cent Cu and conductivity. This is expected as at the cross-hole locations the conductivity signals are weaker in their correlations with copper grades. The correlation differs between cutoff combinations and these differences are reflected in the results discussed below.

**Simulation results and discussion**

The results of the joint geostatistical simulation of per cent Cu and conductivity data are shown in Fig. 6, which depicts two equally probable realizations of copper grades in the cross-hole region. The simulations were run on a grid resolution of 1 m × 1 m. Typically, the simulated orebody grades reflect the actual in-situ grade variability and suggest possible variations of the orebody. For instance, Fig. 6(b) indicates the possibility of the presence of a copper string in the top of the section that is not apparent in the first simulation in Fig. 6(a).

**Fig. 5** Scatter plot of per cent Cu, or primary, versus conductivity, or secondary, data

The figure shows a discontinuous copper string in the upper part of the section between the cross-holes as well as various small copper pockets above the main orebody in the lower part of the section. For comparison Fig. 8 shows the expected copper grade (estimate) in the cross-hole
region derived from the same copper assay data, method and parameters as used for the copper grade modelling in Fig. 7 but without the RIM conductivity data. Several interesting points may be noted. The orebody model based exclusively on the drill-hole data shows a general tendency to link the grades from one drill-hole to another. This appears in Fig. 8, for example, to generate a continuous string of copper in the upper part of the section as well as a more extensive orebody in the lower part of the section. With the additional use of background conductivity data Fig. 7 suggests a less continuous copper string at the top of the section and a more confined orebody in the bottom part of the cross-hole region and shows a more realistic representation of the orebody. As expected, the use of additional, reliable and relevant information can lead to both better delineation of the orebody and accurate representation of the in-situ copper grades and their variability.

Conclusions

An extended joint geostatistical simulation technique can be used to generate orebody models of ore grades that are based on both primary ('hard') and secondary ('soft') data. This is important considering the ever increasing generation of diverse, indirect grade data in mining operations, including in-mine geophysical data that can assist ore delineation, grade estimation and orebody modelling. The application of the method has been demonstrated in the modelling of Cu grades in the cross-hole region in a copper orebody at Mount Isa mine. The copper grade modelling was based on the joint use of Cu grade assays and cross-hole RIM conductivity data. The method presented is general and can be used to integrate most types of geophysical imaging data with the orebody modelling and subsequent mine planning processes. Further improvements to the method and its application could include (i) the enhancement of results from the use of co-located drill-holes and tomograms other than for the cross-holes; (ii) further application of the techniques to additional case studies and in-mine geophysical data types so as to increase experience in the application of the technologies; and (iii) investigation of possible support effects that may arise from the nature of the secondary data.

Acknowledgement

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Fig. 7 Average (e-type) model of Cu grade, %, in cross-hole region generated from 50 simulations based on both DDH Cu assay and RIM-derived conductivity data.

Fig. 8 Average (e-type) model of Cu grade, %, in cross-hole region generated from 50 simulations and based exclusively on DDH Cu assay data.

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References
8. Dimitrakopoulos R., Furrely C. and Godoy M. I'd rather be approximately right than precisely wrong: grade uncertainty, risk effects and decision making in open pit design. In Strategic mine planning 2001 (Melbourne: Australasian Institute of Mining and Metallurgy), 35–42.
22. Stolarczyk L. G. Definition imaging of an orebody with the
23. Verly G. Sequential Gaussian co-simulation: a simulation method
integrating several types of information. In Soares A. ed.
26. Zhu H. Modeling mixtures of spatial distributions with integration

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**EXPRESSION OF INTEREST & CALL FOR PAPERS**

21st Century Pt–Pd Deposits: Current and Future Potential

3–4 January, 2002
Southampton Oceanography Centre, University of Southampton

A special session on Pt–Pd deposits organized by the British Geological Survey (BGS),
the Institution of Mining & Metallurgy (IMM) and the Mineral Deposits Studies Group
(MDSG) within the MDSG Annual Meeting

**Theme**
The buoyant and sustained commodity prices for platinum and palladium have made Pt-Pd deposits highly attractive targets for exploration and investment. While most exploration remains centred on sulphide- and chromite-bearing zones within mafic-ultramafic complexes, there is an increasing recognition that significant Pt-Pd resources may be found in less conventional settings or as valuable by-products with other metals (e.g. in alkaline rocks, porphyries and sediment-hosted deposits). A prime example of a new and poorly understood Pt–Pd deposit is the Platreef, that will account for an increasing proportion of South Africa’s platinum and palладium production over the next 25 years. The aim of this special session is to bring together exploration and mining geologists, engineers and mining analysts who have an interest in platinum and palladium, to review and discuss existing deposits and the potential for finding and developing new Pt-Pd resources for the twenty-first century.

**Keynote Speakers**
Information will be provided in the second circular.

**Submissions**
Participants are invited to submit abstracts (maximum of two A4 pages) for presentation at the meeting. These may cover: (a) descriptions of new or existing deposits; (b) new research on Pt-Pd deposits or processes involved in the development of Pt-Pd mineralization; or (c) exploration/ mining/finance case histories dealing with Pt-Pd deposits. The deadline for receipt of abstracts is the 31 August, 2001. Authors of accepted abstracts will be invited to prepare longer research and professional papers for publication in a thematic issue of the IMM Transactions Section B (*Applied earth science*) in early 2002.

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