QUANTIFYING THE IMPACT OF ADDITIONAL DRILLING ON AN OPENPIT GOLD PROJECT

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Abstract

Multiple conditional simulations are used to evaluate the impact of additional drilling on an open-pit gold project. Based on initial drilling, the mining company was planning a pit about 400m deep, but subsequent drilling suggested that high-grade mineralisation extends downward. Reliable estimates of reserves were available for upper levels but below that the reserves are highly uncertain. So our aim is to develop a methodology for predicting the potential of future drilling, not merely on average but more specifically as a function of the grades obtained in the drilling. To do this, we chose the location for 6 fictive drill-holes (i.e. doubling the information available in the lower part of the deposit). Then 100 sets of grades were simulated for these drill-holes. Following standard practice in the oil industry we selected sets representing an optimistic case (90% quantile), a pessimistic one (10% quantile) and an average one (50% quantile). Fifty block simulations were then run using these as conditioning data. In most but not all cases the average grades obtained with the additional data were less dispersed than without it. The exceptions are particularly instructive because they illustrate that additional information can lead to an increase in uncertainty, which is counter-intuitive.

Key Words: Conditional simulations, sequential updating, geostatistics

1. Introduction

Nowadays multiple conditional orebody simulations are routinely used for evaluating projects in both mining and petroleum. This paper proposes a methodology for assessing the impact of additional drilling on projects, using an open-pit gold mine as a test case. When multiple simulations are used for volumetrics in the oil industry, it is standard practice to run several hundred reservoir simulations and then rank the simulated volumes in descending order and select three typical cases: a pessimistic case (10% probability of being below it), the most likely case (the 50% quantile) and an optimistic case (only 10% probability of exceeding this). These are denoted as P10, P50 and P90. We will show how to transpose this interesting concept to mining. One key difference between oil and mining is that ore reserves depend on two variables, grade and tonnage, rather than one. Our primary objective is to predict the in situ reserves assuming that additional drilling indicates higher than average grades (or average grades or low ones). To be more precise we want to predict the posterior distribution given additional drilling corresponding to the P10, P50 or P90 cases.

The structure of the paper is as follows. After reviewing the existing literature on the applications of conditional simulations in mining and on the concepts of P10, P50 and P90 used in the oil industry, we present the orebody that is being used as a test case (Section 3) and then carry out a standard geostatistical analysis (basic statistics, variography etc) in Section 4. Section 5 describes one of the key steps in this study: setting up the fictive drill-holes and informing them. One hundred sets of grades were generated for these. Five sets of fictive data were chosen to represent the P10, P50 and P90 cases. Fifty block simulations were generated for each of these cases to evaluate the upside and downside potential. To facilitate comparisons an additional 50 block simulations were run using only the original data. Analysis the results (Section 6) showed marked differences between the updated mean depending on the mean of the additional drilling. More interestingly it allowed us to experimentally demonstrate the “Christmas tree” model for the evolution of uncertainty with time (i.e. increasing information). Most people intuitively believe that the variability must decrease as the
number of drill holes increases, unless the initial distribution has been mis-specified. This is incorrect. In fact when plotted against time the variance has a characteristic “Christmas tree” shape. This has important implications in the management of natural resource projects.

2. Literature review

Conditional simulations in mining

When conditional simulations were first developed in the seventies, their main uses were mine planning and grade homogenisation (Journel, 1974; Deraisme (1977) and Marechal & Shrivastava (1977)). Simulations are still widely used for this (see for example, Nowak, Srivastava & Sinclair (1993); Dowd (1994); Sanguinetti, Shrivastava, Deraisme, Guibal & Humphreys (1994); Guibal, Humphreys, Sanguinetti & Shrivastava (1997); Sahin & Fuseni (1998)). In a similar vein, simulations have also been used to compare different sampling patterns. For example, Kleingeld, Thurston, Prins & Lantuéjoul (1997) used a Cox process to simulate the diamond distribution in marine placer deposits in order to test the efficiency of different sampling campaigns and to assign confidence intervals to block estimates.

By the early nineties, the emphasis had moved to evaluating mining projects. In his review paper, Ravenscroft (1994) distinguished between two types of uses of simulations:
- Modelling local short-scale variability in a way not provided by any interpolation technique (e.g. the applications listed in the preceding paragraph),
- Generating equi-probable alternative images of the deposit to allow for sensitivity and risk analysis.

Since then, risk analysis has been one of the leitmotifs of simulation papers. Several authors have focussed on the interaction between geological uncertainty and openpit optimisation (Rossi & Van Brunt (1997); Biver, Mostad & Guillou (1997); Dimitrakopoulos (1997); Rossi & Alvarado (1998); Thwaites (1998); Van Brunt & Rossi (1999) and Coombes, Thomas, Glacken & Snowden (2000)). Simulations can also be used to estimate the global estimation variance for different drilling grids (Humphreys and Shrivastava (1997)). Measuring the global estimation variance as a function of the sample grid helps decision makers choose the most suitable grid size but it does not tell them how much impact additional drilling could have. In this paper we propose a novel approach in which multiple simulations are used to estimate the posterior distribution assuming that the extra holes are

(1) about average (the P50 case), or
(2) richer (P90) or
(3) poorer (P10).

Definitions of P10, P50 and P90 reserves

In the 1980s the oil industry started to introduce probabilistic reserve definitions in addition to the usual “proved” and “probable” categories. According to Ross (1994) a reference to probabilistic methods appears in an appendix to 1987 WPC report on Petroleum Reserves. Murtha (2001) explains what is meant by P10, P50 and P90:

\[ P10 \text{ is the point that would split the area under the curve into 10\% and 90\% of the total area, meaning that there is only a 10\% chance that the reserves are less than the P10 value.} \]

As the distribution of the reserves is estimated from a Monte Carlo simulation model, this means that 10\% of the realisations in the model are less than the P10 value and 90\% are greater. This requires being able to rank the results of the MC simulations in an unambiguous way, which is possible for the reserves but poses problems for productions forecasts because these are a function of time. Murtha (2001) gives examples of production forecasts which one forecast is greater than another in early years but then they cross over.

Problems of a similar nature arise in mining. Because of the shape of the ore-body, it was important to calculate the reserves in the upper and lower parts separately. There are no problems finding the P10,
P50 and P90 reserves for the upper part, or the lower part or the whole deposit, but as can be seen from Fig 1, we need to consider five cases:

1. high grade top, high grade bottom
2. average top, average bottom
3. low grade top, low grade bottom
4. high grade top, low grade bottom
5. low grade top, high grade bottom

Figure 1: Scatter diagram of average grades of the upper and lower parts of the deposit. The values lie in an ellipse. Points N°1, 2 and 3 have high, average and lower mean grades for both top and bottom. The lateral cases N°4 & 5 have high grades in one part and low ones in the other.

A similar situation occurs when both the ore tonnage and metal tonnage are considered for a given deposit. When the scatter diagram of metal tonnage Q versus ore tonnage T is plotted, the first three cases (high Q, high T; average Q, average T; low Q, low T) lie on the regression line and so have similar average grades, with varying tonnages (i.e. mine lives). The other two cases have markedly different average grades and hence a different profit structures.

3. Description of the Test Case: the Eldorado Mine

The problem in the test case can be summarised as follows. Initially the mining company was planning a small pit about 400m deep, but subsequent drilling suggested that high-grade mineralisation extends downward. Drilling gave them reliable estimates for upper levels but below that the reserves are highly uncertain. Figure 2 shows schematic section through the deposit. More than eighty inclined drill-holes intersect the top part of the deposit; only six were drilled into the lower part. So management has several options for developing the deposit including:

- Open up a small pit now,
- Open up a large pit now, with the chance of a larger profit,
- Carry out additional drilling which would reduce the uncertainty on the grades in the orebody extension, but would be costly and would delay the start of the project.

The first option is easy to evaluate. As the upper part of the deposit is densely drilled, there is little variability between the reserves of the conditional simulations (and hence the corresponding NPVs). In that case multiple simulations would add little information. As the second option is inherently riskier, conditional simulations effectively add value by providing the histogram of possible reserves, allowing management to decide whether the upside potential justifies the downside risk.
In order to evaluate the third option we need to quantify the effect of extra drilling before it is carried out. The first question that management would be tempted to ask is how rich (or poor) could the extra drilling be, given the characteristics of the orebody and current levels of knowledge. That is, what are the P10, P50 and P90 scenarios? Then assuming that the drilling is carried out and yields one of these cases (P90 say), how much upside and downside potential is there now? Clearly, if the extra drilling hits low grade material (the P10 case), the updated mean should rise, and conversely if the drilling hits high grade (P90) material. There is no reason to expect the same amount of variability for the three cases.

To sum up we want to assess the posterior distribution of reserves given that extra drilling falls into the P10, P50 or P90 classes. Conditional simulations are the obvious way to tackle this problem. But before doing this we have to decide how many extra drillholes to consider and where they should be located.

4. Basic geostatistics

Stationarity

The next step to determine whether the deposit can be considered as being stationary. The orebody does not continue up to the surface; there is waste above it. Firstly we outlined the mineralised zone (the shaded area in Fig 2). Then to decide whether to consider the gold grades as stationary or not, this zone was divided into a grid parallel to the fault plane and the statistics were calculated for grid squares. As no significant trends were found, either perpendicular to the fault or parallel with it, this zone was treated as being stationary.
Statistics of Raw Data & Anamorphosed Grades

Table 1 gives the statistics of the 2390 samples inside the mineralised zone. The raw grades were transformed to normality before carrying out the simulation. For confidentiality reasons we cannot give full details of the deposit on which this work was based. The grades have been factored.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N°</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grades</td>
<td>2489</td>
<td>0.01</td>
<td>41.14</td>
<td>3.72</td>
<td>4.84</td>
</tr>
<tr>
<td>Upper part</td>
<td>2284</td>
<td>0.01</td>
<td>41.14</td>
<td>3.70</td>
<td>4.86</td>
</tr>
<tr>
<td>Lower part</td>
<td>148</td>
<td>0.01</td>
<td>21.06</td>
<td>3.90</td>
<td>4.68</td>
</tr>
<tr>
<td>Gauss</td>
<td>2489</td>
<td>-2.05</td>
<td>3.56</td>
<td>0.01</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Variogram Model of Grades after Anamorphosis

The experimental variograms of the transformed grades were calculated parallel and perpendicular to the fault plane. The fitted model consists of 3 structures: a spherical structure that describes the behaviour for small distances and two exponential structures. Its parameters are given in Table 2.

<table>
<thead>
<tr>
<th>Sill</th>
<th>Range 1(m)</th>
<th>Range 2(m)</th>
<th>Range 3(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spherical 1</td>
<td>0.05</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Exponential 1</td>
<td>0.75</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>Exponential 2</td>
<td>0.20</td>
<td>400</td>
<td>400</td>
</tr>
<tr>
<td>Rotation</td>
<td>-165°</td>
<td>45°</td>
<td>150°</td>
</tr>
</tbody>
</table>

(The rotation is indicated in the geological convention, relative to east)

5. Using simulation to mimic additional drilling

Having completed the variographic study, we are now ready to start the ore-body simulations. The procedure followed can be divided into seven steps:

(a) Choose the number of fictive drill-holes and their locations
(b) Run 100 point simulations of values on drill-holes
(c) Calculate the average grade of fictive plus real drill-holes for each simulation (a) for upper part of ore-body and (b) for lower part
(d) Plot scatter diagram of these 100 pairs of averages, and find the 5 cases listed above
(e) Run 50 block simulations for each of these 5 cases
(f) Run 50 block simulations using only original data
(g) Analyse the results
Simulating the grades on the fictive drillholes

Only six drill-holes intersect the lower part of the deposit. It was decided to double the number of holes in that part of the deposit by adding six fictive holes located about halfway between the real ones. One hundred conditional simulations were run to inform the points on the six fictive drill-holes, using the turning bands approach. Ordinary kriging was used to condition them. The mean grades of the upper and lower parts of the mineralised zone were calculated for each of the 100 simulations. Figure 2 presents the 100 pairs of means as a scatter diagram.

![Figure 2: Scatter diagram showing the mean of the real + fictive drill-holes in the upper part of the deposit (on vertical axis) versus their mean in the lower part. (Note the vertical scale is exaggerated compared to the horizontal one)](image)

Five typical cases were selected as described earlier. Table 3 gives the statistics for the real plus fictive drill-holes for the upper and lower parts, for these five simulations together with the corresponding statistics before adding the fictive drillholes. As expected, the extra holes have much less effect on the densely sampled upper part.

**Table 3: Statistics of the data in the upper and lower parts of the deposit.**

<table>
<thead>
<tr>
<th></th>
<th>Upper Mean</th>
<th>Upper St Dev</th>
<th>Lower Mean</th>
<th>Lower St Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial 90 holes</td>
<td>3.70</td>
<td>4.86</td>
<td>3.90</td>
<td>4.68</td>
</tr>
<tr>
<td>Simu 22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rich upper</td>
<td>3.80</td>
<td>5.07</td>
<td>4.93</td>
<td>5.83</td>
</tr>
<tr>
<td>Rich lower</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simu 14</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average upper</td>
<td>3.69</td>
<td>5.06</td>
<td>4.18</td>
<td>5.50</td>
</tr>
<tr>
<td>Average lower</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simu 81</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor upper</td>
<td>3.60</td>
<td>4.78</td>
<td>3.33</td>
<td>4.04</td>
</tr>
<tr>
<td>Poor lower</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simu 41</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rich upper</td>
<td>3.79</td>
<td>5.23</td>
<td>3.80</td>
<td>5.11</td>
</tr>
<tr>
<td>Poor lower</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simu 54</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor upper, Rich lower</td>
<td>3.55</td>
<td>4.91</td>
<td>4.69</td>
<td>6.32</td>
</tr>
</tbody>
</table>
Running 50 conditional simulations for each of the five sets of real + fictive data

The next step consisted of running 50 conditional simulations on blocks of size 10 x 25 x 10 m, using each of the five sets of real + fictive drillholes as conditioning data. To distinguish these simulations from the preceding ones we will refer to them as the “descendants” of the corresponding “parent” set of data. For comparison purposes 50 block simulations were run using only the original drill-holes as conditioning data. During the analysis of the results we decided that it would also be interesting to see what happened for a really extreme set of fictive + real data. So we ran a further 50 block simulations for the set with the highest mean, Simu55.

6. Results

Figure 3 shows the histograms of the 50 means of the lower part of the deposit, for the various sets of simulations. Table 4 gives the statistics of the means for the lower part of the deposit for each set, with the average value of conditioning data shown in brackets below it. Firstly we see that the average of the 50 simulations is not equal to the mean of the conditioning data. The simulations tend to be drawn toward the overall mean, 3.90. Because of our assumption of stationarity, we kept the same variogram model and the same anamorphosis even after adding the fictive data. When the gaussian equivalents were being back transformed to the initial scale after the simulation, they were scaled relative to the coefficient of the first Hermite polynomial which was set equal to the mean of the data of the original 90 drill-holes (i.e.3.90).

Table 4: Statistics of the means of the 50 block simulations in the lower part of the deposit, descending from the 5 sets of real + fictive data, for the simulations obtained using only the original data and for the most extreme set of fictive + real data, Simu55. The mean of the real + fictive data used to condition the simulations is indicated in brackets.

<table>
<thead>
<tr>
<th>Lower Part</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>St Dev</th>
<th>10%</th>
<th>50%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simu22</td>
<td>2.83</td>
<td>5.75</td>
<td>3.94 (4.93)</td>
<td>0.59</td>
<td>3.29</td>
<td>3.85</td>
<td>4.60</td>
</tr>
<tr>
<td>Simu14</td>
<td>2.65</td>
<td>5.60</td>
<td>3.80 (4.18)</td>
<td>0.64</td>
<td>2.99</td>
<td>3.75</td>
<td>4.56</td>
</tr>
<tr>
<td>Simu81</td>
<td>2.16</td>
<td>4.97</td>
<td>3.45 (3.33)</td>
<td>0.59</td>
<td>2.86</td>
<td>3.36</td>
<td>4.08</td>
</tr>
<tr>
<td>Simu41</td>
<td>2.17</td>
<td>4.18</td>
<td>3.25 (3.80)</td>
<td>0.45</td>
<td>2.78</td>
<td>3.26</td>
<td>3.83</td>
</tr>
<tr>
<td>Simu54</td>
<td>2.94</td>
<td>4.94</td>
<td>3.77 (4.69)</td>
<td>0.49</td>
<td>3.21</td>
<td>3.67</td>
<td>4.42</td>
</tr>
<tr>
<td>Simu</td>
<td>2.46</td>
<td>5.09</td>
<td>3.93 (3.90)</td>
<td>0.54</td>
<td>3.16</td>
<td>4.06</td>
<td>4.69</td>
</tr>
<tr>
<td>Simu55</td>
<td>2.85</td>
<td>6.15</td>
<td>4.01 (5.50)</td>
<td>0.63</td>
<td>3.35</td>
<td>3.87</td>
<td>4.66</td>
</tr>
</tbody>
</table>
Figure 3: Histograms of the average grades of the 50 simulations obtained using the 6 sets of fictive + real data, and the histogram of 50 simulations obtained from the original 90 drillholes.
Figure 4: Cumulative distributions for the means of the 50 block simulations that are descendants of simulations No 14, 22, 41, 54 and 81.

Interpreting the results

Plotting the cumulative distributions for the sets of simulations facilitates the analysis of the results. These curves allow us to answer questions like:

(a) What is the possible range for the average grade of the lower part if the additional drilling turns out to be like the P90 case (or the P10 or the P50 case)?
(b) How much above and below this could the reality turn out to be?
(c) Will the dispersion of the average grades be the same for all the descendant sets?
(d) Intuitively we expect the dispersion to decrease as more information becomes available. Is this always true?

The first observation concerning the 5 cumulative distributions shown in Fig 4 is that the curves are, in general, separate. This is not always so. Simu81 and Simu 41 correspond to the low grade cases. As expected, their cumulative distributions shown in blue and purple respectively have consistently lower grades than the others. Conversely the descendants from Simu22 (pink) are consistently richer. Looking at the grades that correspond to 0.05 and 0.95 for the blue and purple curves, we see that the average for the lower part could range from about 2.5 to about 4.0. This means that if the additional drilling turns out to be low grade (P10), we could expect the (true) mean of the lower part of the deposit to lie in the interval from 2.5 to 4.0. Similarly if it had turned out to be high grade (P90), the true mean could be expected to lie between 3.5 and 4.5.

Suppose that an average grade of 3.5 (say) is critical for profitably mining the lower part. Looking at this value on the X axis, we see that for the blue curve, 60% of the means are below 3.5 whereas for the pink one about 80% are above it. This can be interpreted as meaning that for the P10 case there is only 40% chance of the average grade being above 3.5 compared to 80% for the P90 case. So this procedure gives management an objective way of assessing the upside (P90) and downside (P10) potential of the deposit after drilling an extra six holes.
Comparing the statistics with and without the extra drill-holes

The best way of assessing the impact of the additional drilling is by comparing the simulation results obtained with extra drilling to those obtained using only the original data. The statistics of the means of the 50 block simulations (Table 4) are comparable to those of the 5 sets of data, and likewise for its histogram (Figure 3). Figure 5 shows their cumulative distribution in light blue, together with those for Simu22, Simu14 and Simu81. It is further to the right than had been expected.

Figure 5: Cumulative distributions for the means of the 50 block simulations obtained from the original 90 drill-holes (light blue). For comparison purposes those for Simu22 (P90), Simu14 (P50) and Simu81 (P10) have also been included. The cumulative histogram for the descendants of Simu55 (P01) is shown in purple.

Considering an extremely rich case (P99)

Initially 100 conditional simulations were constructed in order to generate the data for the fictive drill-holes. We now focus on the largest one (i.e. the P99 case). Using the standard statistical criteria this can be considered as exceptionally large; it effectively lies outside the 95% confidence limits and yet it was generated in exactly the same way as the others. This case will be used to illustrate what happens when a statistically “unexpected” result occurs. The mean and the quantiles are consistently higher than those for the other five sets and the standard deviation is also larger (Table 4).

Evaluating the Impact of Additional Drilling

Most people intuitively expect that uncertainty will decrease as additional information becomes available. They believe that the uncertainty can increase only if the initial model was mis-specified; for example, if the model underestimated the inherent variability. Figure 5 summarises expectations. In fact this preconception is mistaken. Galli et al (2001) prove that this is theoretically incorrect. Additional uncertainty can increase even when the model is correctly specified. A “sideways Christmas tree” model of uncertainty (Figure 6) is proposed, in which the uncertainty decreases as information becomes available up to a certain time where “unexpected” information is received. At that point, the predicted mean changes; it need not lie within the previous confidence limits. More importantly, the confidence band widens. We now illustrate this using the information from the simulations.
As well as showing the evolution in uncertainty that most people intuitively expect (top left), Figure 7 presents the change in the simulated mean value of the lower part of the deposit as predicted by the simulation study, for three cases: Simu22 (P90, bottom left left), Simu81(P10, bottom right) and Simu55 (P99, top right). The blue squares on the left of each diagram indicate the range of values obtained in 50 block simulations based on the initial 90 drill-holes. Those on the right give the results after doubling the number of holes from 6 to 12 in that part of the deposit. From top to bottom the squares show the value of the maximum, the 90%, 50% and 10% quantiles and finally the minimum. The results for Simu22 (top left in green) agree with our intuitive expectations: additional drilling reduces uncertainty. In the top right corner, the three quantiles and the minimum are as expected but the maximum observed with the extra drilling is well above the value with only half as much drilling and in the lower figure all the statistics show a marked drop. The 50% quantile is almost as low the 10% one before.
Figure 7: The four diagrams summarise the change in the simulated mean value of the lower part of the deposit. The blue squares on the left indicate the range of values obtained in 50 block simulations based on the initial 90 drill-holes. Those on the right give the results if the extra drilling was rich (P90, bottom left), very rich (P99, top right) or poor (P10, bottom right). The diagram (top left) illustrates the intuitive idea that uncertainty decreases as more information becomes available. From top to bottom the squares show the value of the maximum, the 90%, 50% and 10% quantiles and finally the minimum.

7. Conclusions

During the exploration and evaluation of mines and oil fields, management are often faced with the problem of whether to go ahead with additional drilling. In order to decide, they need to evaluate the potential of additional drilling before the results become available. In statistical terms they are looking for the posterior distribution conditional on data yet to be obtained. There are two ways of tackling the question: theoretically in a Bayesian framework or experimentally by multiple simulations. Current research focuses on the simulation approach. In this paper on an opencut gold mine, ninety drillholes were available at the outset of the study so geostatistical simulations were the obvious way to tackle the question. In a parallel paper (Galli et al, 2001) on a satellite gas field where only one well was available in addition to the seismic profiles, we developed a probabilistic model for the reservoir shape (a tilted block cutoff by a sealing fault). In that case, our aim was to quantify the impact of drilling one or two extra wells. Both papers address the question of sequentially updating the reserves.

The first step in predicting the impact of additional drilling is to decide on the location of the extra holes; the next is to determine what is a reasonable range for the grades obtained. Nowadays it is standard practice in the petroleum industry to quote three figures for reserves: the P90 and P10 values in addition to the expected value. Following this practice we have used the 10%, 50% and 90%
quantiles on the means of the simulations to guide as to what sort of results are plausible. Clearly the assumption of stationarity (or nonstationarity) is critical. The mean (and to a lesser extent the sill of the variogram) have an impact on the simulations.

A careful analysis of the sets of 50 block simulations showed that the range of uncertainty narrows, in most cases, as a result of the extra information as would be expected. But this is not always true. Sometimes the confidence band widens out even if the data is compatible with the model used before the updating. Figure 7 shows one case (bottom left) where the uncertainty was reduced. In the other two cases it does not. For the case in the top right, the maximum jumped well above that seen before updating whereas in the bottom right case, the mean dropped sharply and so do all the quantiles. In all three cases the simulations were in fact compatible with the earlier model, because of the way they were generated. This confirms the “sideways Christmas tree” model (Fig 6). Its implication for management are important. At present, decision-makers expect additional sampling to reduce uncertainty. The Christmas tree model highlights the need for lateral thinking when planning the development of projects. This is particularly vital as companies try to shorten the lead time between exploration and production.

8. References


Marechal, A. & Shrivastava P. (1977) Geostatistical Study of a Lower Protozoic Iron Orebody in the Pilbara Region of Western Australia, 15th APCOM Symposium, Brisbane Australia, 4-8 July 1977, pp221-230


Ross, J.G. (1994) Discussion of the Comparative Reserves Definitions: USA, Europe & the former Soviet Union, JPT August p 713, SPE 28020


