Introduction

For years those in the minerals industry have been taking samples to assist them in making decisions; whether they be about investing billions of rand in a new mining operation, or simply directing a truck load of mineralized material to the mill or the waste dump, we need a sample to aid our decision making. This paper emphasizes the importance and significance of sampling as a process, some of the associated technical problems and some of the advantages, especially in the light of traditional approaches that has usually left mine sampling to the least educated and lowest paid individuals on the mine.

Perhaps the most important aspect that requires attention is the variability, usually measured in terms of precision that tends to infect the sampling procedures. Francis Pitard (Pitard, 1993, 2002, Ingamells and Pitard, 1986) has stated: ‘There is no such thing as reliable feasibility studies, unbiased ore grade control, accurate environmental assessments or effective process control, if you cannot identify and minimize the seven major sources of sampling variability.’ At the time this statement was made Gy’s seven sampling errors were well known and established in the literature. Since then the number of recognized error has expanded to ten, and it is these ten sources of sampling variability and the way they arise that are briefly investigated.

Variability is measured in terms of variances and rather than being self-compensating, there is good evidence to indicate that they are in fact additive at every step in the sampling and analytical process.

Mineral development process

The three main processes in mineral development that include exploration, followed by technical analysis, and the financial
There are many questions needing answers concerning the sampling procedures and processes. For example, how good a sample is 1 kg of rock with 1 cm top-size fragments? If the lab crushes my gold ore sample to 10 mesh (1.7 mm) and takes a 500 g split, is this always OK? How would the lab know? How much money should be spent on sampling and sampling equipment? And what is the impact of lousy sampling and assaying on the annual profit of a mine? For a typical sampling event on a mine the question might be, 'How do we go from a 50 t truck load of ore to a 50 g aliquot for a fire assay, without losing precision?'. This will probably involve seven or eight steps along the way and each step must aim to preserve the integrity of the sample.

In order to replace these questions with confident answers about the sampling procedure, a sampling nomogram is required that describes and summarizes the relationship between the fragment size, the mass of the sample relative to the mass of the lot and the relative variance that can be anticipated. The nomogram is in fact a graphical representation of Gy's famous formula that describes the relationship between sample variance, known as the fundamental error (FE), the nominal size of the fragments, and the mass of the sample, as follows:

\[ \sigma_{FE}^2 = \frac{K d^2}{M_s} \]  \[ \text{[1]} \]

where \( K \) is a constant sampling parameter related to the nature and heterogeneity of the material being sampled, \( d \) is the nominal top-size in centimetres of the fragments being sampled at 95% passing a given screen size, and \( M_s \) is the mass of the sample in grammes. Taking logarithms of both sides of Equation [1] gives:

\[ \ln(\sigma_{FE}^2) = \ln\left(\frac{1}{M_s}\right) + \ln(K d^2) \]  \[ \text{[2]} \]

\[ \ln(\sigma_{FE}^2) = (\pm 1)\ln(M_s) + 3\ln(d) + \ln(K) \]  \[ \text{[3]} \]
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Equation [3] can be used to build a chart, which shows that for a given stage of comminution (i.e. a fixed value of particle size $d$), the term $\ln(K) + \alpha \ln(d)$ is a constant say $c$ ($\beta$) and:

$$\ln \left( \alpha \right) = -\ln \left( M_s \right) + c \left( d \right).$$

So for any given fragment size $d$, this is a line with a slope of $-1$.

An example of such a nomogram is shown in Figure 2. The most important objective in the sampling process is to obtain a representative sample, something we can achieve only through random sampling. The random sample must be one that is unbiased. However, while it is easy it is to demonstrate that a bias exists, it is theoretically impossible to demonstrate its absence. Poor sampling protocols lead to the introduction of random errors and biases, and try as you may, what we normally get will probably be inaccurate and imprecise. Figure 5 illustrates the idealized concepts relating to accuracy and precision, the ideal sample being one that is both accurate and precise. In reality this rarely happens.

It cannot be overemphasized that what we want is statistically random sampling. This means that 'every particle in the lot has the same chance as every other particle in the lot of being in the sample', but the application of this principle is more difficult to implement than it appears.

The SAMREC Code (2007) requires that: ‘...a Competent Person reporting Mineral Resources must have sufficient knowledge of sampling and assaying techniques relevant to the deposit under consideration to be aware of problems that could affect the reliability of the data. Some appreciation...’

Not only that, but he must ensure that QA/QC verification has been undertaken for all assays and analyses. As our appreciation of the problems associated with sampling and assaying deepens, it is becoming evident that this is a realm of enormous uncertainty in many mining operations.

The sampling protocol in technical evaluation

A significant problem faced by the mining industry is the aspect of reconciliation, which is measured in different ways at the various points along the mining-beneficiation route. Examples of reconciliation points include the mine call factor, the balance between residues, tails and the metallic product, the audit of product versus customer specifications, and the overall reconciliation, mass balance and metal accounting through the plant. Pitard (2006) has stated that this can often lead to endless meetings to solve puzzles, arguments and finger pointing, correcting factors are applied until data fits normality, geologists and geostatisticians cannot do their work, miners and metallurgists are at war, the company’s performance deteriorates, management is not happy, and to cap it all the market share value goes down. But this unhappy process can be reversed through education and training in the theory and methods of sampling for those involved and affected by the sampling outputs. This would include management, board members, shareholders, geologists, drillers, miners, metallurgists, analytical chemists, statisticians, and dare I say it, even the sales staff. Detailed understanding may not be necessary for everyone, but a good look at correct sampling protocols together with data verification can lead to improved metal recovery, closer reconciliation between mineral inventory estimates and metal output, which in turn lead to better cash flows, enhanced profits and added share value (Pitard 2006).

Generally sampling conducted on mining operations is a highly structured procedure or protocol, with the sampler knowing exactly what is required. Samplers identify the reef, the footwall and hanging wall and using either a diamond...
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saw or a chisel they then cut a channel, ensuring that exactly two centimetres of material are collected in the waste rock on either side of the reef. Depending on the difference in hardness and friability across the reef they will take either more or less of certain parts of the reef, and fill a bag with about 300 g of reef material.

While this part of the protocol is rigid and fixed in most samplers’ minds, it is unlikely that they know that the aim and object of the exercise is to collect a truly representative sample, to minimize bias, and to minimize the error variance. Beyond this point the sampler is probably oblivious of what takes place in the laboratory and how important his first steps in simply collecting the reef sample are to a meaningful outcome of the sampling process. This of course is just one sampling position and many different types of samples, including solids and liquids occur at many different localities in a mining and milling operation.

A relatively important aspect of the sampling protocol is that those involved understand the need for and the importance of the sampling nomogram. This representation is the optimal balance between the mass of the sample (including primary sampling onsite), the degree of comminution, the effort expended on splitting and division and ultimately arriving at a sampling aliquot that has followed a route that minimizes the error variance of the estimate. But all this takes time and resources, both of which equate to money.

Any sampling protocol should seek to optimize the processes of sample delineation, sample extraction, sample preparation and sample analysis, providing exact information about the mass of material required for the sample, the degree of comminution, the degree of division, and ultimately the mass of the aliquot of material for final analysis. Those taking the samples need to be aware of the total procedure if their sampling is to be guided in an educated manner. However, it is essential that the sampling parameters that characterize the reef be fully understood.

The scale of variability

The quote from Francis Pitard highlights the importance of understanding variability. Understanding the total variability requires that we split the variance up into its component parts and evaluate each one individually. Pierre Gy initially identified that there is a small-scale component and a large-scale component of variability. The small-scale component is related to the nature of the ores and specifically what we refer to as the constitutional and the distributional heterogeneity of the ores. It is these characteristics that give rise to the fundamental error (FE), the nugget effect (NE) and the grouping-segregation errors (GE). Understanding of these types of variability enables us to both compile and implement optimized sampling protocols. The important issue in small scale variability is that having once established an optimal sampling protocol, the protocol must be implemented; in other words it’s no good just hearing about this good news, you must do it as well.

While large scale variability is closely linked to the sampling characteristics of the ore, it also involves local and regional trends and structures in exploration, patterns of variation in long-term mine and mill related processes of materials balance, reconciliation and metal accounting, and statistical process control related to product specifications and trade in commodities. The importance of the large-scale variability in understanding metallurgical plant behaviour and metallurgical balances is starting to be appreciated through the application of the semi-varigogram to the analysis of problems in the process plant. The range and types of errors that have been identified in the sampling procedure are shown in Figure 4.

In diagrammatic fashion (Figure 5) Francis Pitard (2005) has shown how these errors relate to one another. These are accumulated variances at different levels with heterogeneity (a combination of the nugget effect due to coarse-grained gold, the fundamental error, and the grouping and segregation error), being the core variance. The delimitation and extraction errors, the weighting and preparation errors, as well as the analytical error are also contributors.

Of special note here is the term V[0] which Pitard (2005) identified, as being the receptacle for all ear-marked sampling errors as well as all random, stray, unidentified, and unaccounted for errors that arise during the sampling process.

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1. The nugget effect (NE): Due to inherent variability of the ore due to true nuggets and clustering of small grains, as well as random, vagrant and unaccounted for sampling errors.
2. Fundamental error (FSE): Due to inherent constitutional heterogeneity of materials; can be minimized through establishing an appropriate protocol, but never eliminated.
3. Grouping/segregation error (GSE): Due to action of gravity on components of different density in sampled material; can be minimized by homogenization and incremental sampling.
4. Delimitation error (DE): Due to failure to correctly evaluate the appropriate sampling dimensions of the lot; sample geometry incorrectly defined. Correct delimitation requires every fragment to have equal opportunity of being selected during the sampling event.
5. Extraction error (EE): Due to failure to correctly extract the correctly delimited sample; usually due to inappropriate sampling equipment.
6. Weighting error (WE): Due to incorrectly positioned or calibrated weightometers.
7. Preparation error (PE): Due to any human or mechanical interference with the integrity of the sample.
8. Analytical error (AE): Due to errors arising from analytical procedures.
9. Periodic process variation (QE1): Periodic fluctuation error changes over time due to day-night temperature variations, timing of sampling where sampling events that have the same frequency as the process variation will not reveal the whole process, some periodic variation may be identified by plotting the data on a time-series analysis.
10. Non-periodic process variation (QE2): Random, non-random and cyclical variations, non-random errors due to shifts or trends in the process or random errors associated with FSE and GSE.

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Figure 4—The ten sampling errors of Pierre Gy, their source and areas of influence
The term commonly referred to as the nugget effect in geostatistics is therefore more than simply ‘inherent random variation’; it includes the components of sampling error and, specifically, a high nugget effect may be telling you that your sampling errors are significant. According to Pitard (2006) the in situ nugget effect therefore includes the inherent random variability, correctly identified by geostatisticians as the nugget effect, a variance associated with the specific ore type, but he also identified the fact that it becomes a dumping ground and receptacle for all other types of random and otherwise unaccounted for errors, some of which may be large.

The formula that Pierre Gy is famous for relates the variance of the fundamental error to the product of a series of sampling constants (cfrg) and the nominal fragment size, divided by the mass of the sample. So the variance is directly proportional to the size of the fragments and inversely proportional to the mass of the sample as shown in Equation [1].

A sampling nomogram allows one to present and interpret the relationships among the three main variables namely the relative variance, the fragment size, and the mass of the sample on a two dimensional chart. Some of the constants used in Gy’s formula are sample specific and can be determined by performing what is known as the ‘heterogeneity test’, a gold deportment study, and some basic mineralogy. With these kinds of information it is possible to compile a sampling nomogram, shown in Figure 2, which provides a detailed step-by-step protocol of how the sample should be crushed and split in order to preserve integrity and ensure representivity of the final aliquot accepted for assaying. The nomogram in Figure 2 provides a specific ‘recipe’, if we can call it that, for crushing and grinding so that the error variance is minimized.

The kind of information that can be derived from the analyses performed during a heterogeneity test includes a measure of the variance of fragments at 1 cm diameter. This allows Gy’s formula to be simplified and together with appropriate mineralogical work, it is possible to compile nomograms that specify the relationship between the nominal fragment size and the mass of material required for the sample as well as indicating the mass of material required to keep the sampling variance below an acceptable threshold, as shown in Figure 6.

Figure 5—Relationship between the eight small-scale errors of Pierre Gy. Source: Pitard, 2005, 2006

Figure 6—Relationship between sample variance and sample mass (source, Software by Pitard, F.F., 2005)
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The careful diligent work of the sampling team, the assay laboratory, and assay laboratory manager, who is consistently monitoring the QA/QC audits and processes, cannot be replaced. As a group this segment of the mineral development team provides the base data on which all future decisions are made. If we don’t get it right here we don’t get it right anywhere.

Having once established the protocol it is essential that it be implemented in an appropriate manner so that we take ‘the representative sample’. Implementing the protocol is underlaid by the statistical requirement that ‘any fragment in the lot to be sampled has an equal opportunity to be selected in the sampling event as any other fragment’. Furthermore it means that sample definition (delimitation), extraction, preparation and analysis must follow a rigorous routine that is applied equally to all samples.

The hidden costs of sampling errors

The mass of the samples

Consider the basis on which some of the largest capital commitments in the world, that is in the mining industry, are made. The total capital cost of bringing a mine into production or develop a new mining operation range from R2.01 billion (US$215 million) spent over a period of 12 years for the Target Gold Mine (MT, 2007), to R2.52 billion (US$270m) for the 7-year investment from exploration to start-up for the Cerro Vanguardia Gold and Silver Mine, Argentina (MT, 2007). It is useful to consider the kinds of information on which such decisions are based.

The spread of data shown in Figure 7 is known as the GASA data-set, introduced in 1983 as a freely available, three-parameter lognormally distributed data-set of 27 borehole intersections from which geostatisticians could both compare and reproduce one another’s results. The area covered by the 27 boreholes has not been calculated in detail, but represents about 24 km² and let’s assume that the reef intersections are 1m thick, and that the bulk density of the reef is 2.78 t/m³. The total amount of reef buried at depth would be about 67 Mt (assuming zero reef losses, area is on plane of reef, constant width and no selectivity).

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Assume further that the core is standard NQ type with a diameter of 46 mm, meaning that each one-metre intersection would weigh about 4.62 kg and that in total we would recover about 125 kg of reef from the in situ mass of 67 Mt. This represents 1.86 x 10⁻⁷% of the mass. It is difficult for us to conceive of just how small that number is, but the average 500-seater auditorium has an estimated volume of about 9,000 cubic metres, which is about 9 billion cubic centimetres. A cube with a side of 12 cm provides an idea of just how small that number is, but the average 500-seater auditorium has an estimated volume of about 9,000 cubic metres, which is about 9 billion cubic centimetres. A cube with a side of 12 cm provides an idea of just how much material has been extracted to represent the volume of the room.

However, that’s not all. At the end of a very careful preparation protocol the analyst will extract exactly a 30–50 gramme aliquot of material from the finely milled powder for fire assay. Twenty-seven such assays would amount to just 810 grammes of rock powder. One tonne is equivalent to 1 000 000 g, so 810 g is 0.00081 t to evaluate 67 Mt of rock. Putting that in context means that we are trying to represent

the 9 billion cm³ in this auditorium using a volume about the size of a pinhead. We may think this is exaggerating, but a bad protocol, incorrectly implemented for blast hole sampling, cost a mine US$134 000 000 over a 10-year period (Carrasco et al., 2004), and in another case incorrect sampling of the tailings in a floatation plant cost a mine US$2 000 000 000 over a 20-year period (Carrasco, 2003).

Poor sampling protocols

In four very interesting case studies Carrasco et al. (2004) quantify the losses associated with poor sampling protocols and emphasize the importance of correct sampling protocols and equipment. They describe the benefits of installing a sampling station for the tailings grade and pulp density in a large copper operation in Chile. This state of the art installation proved that the traditional metallurgical balance of 0.15% Cu was too low by 0.05% Cu, a seemingly insignificant amount. However, the daily tailings discharge of 96 000 tons carried away approximately 17 500 tons of unaccounted for copper every year, over a period of 87 years. Thus poor sampling translated into a US$2.2 bn loss for the mine, incorrect decisions over the years, and suboptimal exploitation of the mineral resource.

In the case studies Carrasco et al. (2004) have calculated the net present value of the mining operation according to a method proposed by Matheron (1963), as follows:

\[ Bi = \left( V(m) - p(i) \right) \cdot t^{-\delta} - I \]

where: \( Bi = \) net present value (US$m), \( V(m) = \) the value of 1 ton of ore (US$m), \( p(i) = \) cost of production of one ton of ore, \( t = \) annual rate of production (t/year) = 30 years, \( I(t) = \)
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investment, \( i = \text{discount rate} = 10\% \), \( N = \text{life of mine in years} \), \( m = \text{mean grade above cut-off grade (} \%\text{Cu}) \), \( V(m) = 22.04\times \text{copper price}\times \text{metallurgical recovery rate}\times \text{mean grade} \).

In another case study Carrasco et al. (2004) describe how incorrect blast hole sampling and poor grade control at a porphyry copper deposit resulted in hidden financial losses of about US$22m. They describe how huge fundamental errors are generated as a result of a primitive ‘by hand’ sampling protocol, used to collect a 250 g sample from a 2-ton lot with a nominal fragment size of 2 cm. Biases arising from delineation and extraction errors are also introduced. This disabling sampling protocol arose from an illusion of apparent geological homogeneity of the orebody, the speed with which samples can be collected, and the low costs involved. Geostatistical analysis of the data collected for grade control purposes indicated a nugget effect that constitutes about 70% of the total variance. Compared to analyses of drill core with a much smaller support and a much lower variance, it is clear that poor sampling introduced variability in the form of an artefact nugget effect that does not exist in the orebody.

Even with a carefully designed and implemented sampling protocol it is difficult not to lose metal to the waste dump. So how much more when there is no attempt to implement a proper protocol? Carrasco et al. (2004) also point out that attempts to reconcile mine and mill grades is naïve. Conditional bias dictates that the mine grade must be higher than the mill grade because at least some proportion of waste goes to the mill and a nearly equal proportion of ore goes to the waste dump. Applying constant mine-correction factors is also a ruse that mining men use to placate their consciences.

In their fourth example Carrasco et al. (2004) consider the losses incurred because of the introduction of new technology and failure to calibrate the instruments. This arose because of a marked difference in the geological matrix of the samples and the calibrating standards that introduced a bias of 0.06% copper. Given an extraction rate of 32 Mt per annum, 80% recovery, and a copper price of US$1 per pound, the losses amounted to US$292m over a period of 20 years. This case study emphasizes the importance of diligent and rigorous quality assurance and quality control in the assay laboratory.

As much as two billion dollars can be lost over the 20-year life of a sizable mining operation because of poor sampling practices. Carrasco et al. (2004) cite economic inefficiencies, unsustainable exploitation, and unnecessary externalities as the consequences of improper sampling and assaying practices. Application of the principles of the theory of sampling, a statistical approach to mineral estimation, a chrosostatistical approach to process control and an alignment of company objectives and operational excellence can lead to the identification of hidden losses and improved productivity.

The negative side effects of poor sampling are significant. The most important aspect of a sample, one often overlooked and ignored, is that a sample is simply a proxy for a larger volume of material. Where mining operations take large numbers of samples per day or over a month, the reason, purpose, value, and information content of the sample can often be devalued. Perhaps the most damaging effect of poor sampling is that those who interpret the sampling results and apply the derived knowledge are not fully aware of the information content of the samples. Provided the sample values lie within an acceptable range of variability, there is little further use for them; they simply provide comfort to the plant superintendent that everything is OK. Perhaps the most important improvement that can be made is a renewed appreciation of the information content of sampling data.

The hidden costs of poor sampling are elusive and difficult to find even when accountants scrutinize the balance sheet; consequently, top management fail to appreciate the magnitude of the losses. The costs of poor sampling translate into misclassification of ore as waste and waste as ore, poor metal recoveries, poor reconciliations between in situ grades and metal produced, and distorted material balances. Poor appreciation of the information content of sample data, together with the hidden costs, and the effects of poor sampling are interpreted as poor management of the mine or mill. They are usually accompanied by strong accusations of wasteful behaviour and under performance. The problem is related to a failure to understand the impact and effects of variability on mining processes at different scales of observation. This is directly related to the volume variance effect (also known as the regression effect or conditional bias). Sources of variability are also not well understood and lack of communication between various sections of the mine, the mill, and the vendors of final product means that sections of the operation take on a silo mentality that sees only their portion of the operation as relevant.

The volume-variance effect

The volume-variance effect is variously known as the ‘regression effect’ and ‘conditional bias’, and is a combination of two effects, namely the support effect and the information effect (Armstrong, 1998), which are closely related to one another. Some of the problems arising from the volume-variance effect are illustrated in Figure 8.

The support effect

The support effect and relates to changes in the size of the SMU. Assume that there are 16 one-hundred ton blocks of ore in the floor of an open pit operation containing a total of 6.4 kg of metal. Assume further that if the true grades of these blocks were known that they would have average grades such as those shown in (a) in Figure 8. Together the 16 blocks have a mass of 1 600 t with an average grade of 4.5 g/t metal (7.2 kg in total), and a variance of 6.8 g/t².

Also assume that the economics of the mining operation require a cut-off grade of 3.5 g/t ore with grade higher than 3.5 g/t is sent to the mill, while material with less than 3.5 g/t is sent to the waste dump. If it were possible to correctly apply the cut-off and to evaluate, define and extract these blocks, then 9 one-hundred ton blocks with an average grade of 6.33 g/t would be mined, and with 100 per cent extraction, would yield 5.7 kg of metal. This represents extraction at the smallest SMU.

If the SMU is increased to a 400 t block, that is the support is increased fourfold from a 100 t to 400 t block, the average grade of all the blocks remains the same at 4.5 g/t, but the variance decreases to 1.67 g/t². Applying the same cut-off grade of 3.5 g/t metal, means that 1200 t are
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extracted with an average grade of 5.0 g/t. Thus with less selectivity, and a lower variance, more tons with a lower average grade are extracted, but the total metal recovered increases from 5.7 kg to 6.0 kg as shown in panels (a) and (b) of Figure 8, something every miner would welcome. Thus simple changes in the size of the SMU can affect selectivity as well as the grade and tonnage of ore sent to the mill.

However, if the cost of mining is considered, a different outcome is evident. Assume that it costs 300 g of metal to mine and process each 100 t block. In the first scenario the 9 blocks at 300 g will cost 2.7 kg of metal to mine and process. If our total revenue is 5.7 kg, the operation will realize a profit of 3.0 kg of metal. In the second scenario assume that the mining and processing costs remain the same, but we now have the equivalent of 12 blocks that cost 3.6 kg. The total revenue is 6.0 kg, but with costs of 3.6 kg the profit is only 2.4 kg of metal, a decline in profit of about 10 per cent.

The information effect

A second problem known as the information effect relates to the level of available information at the time when the selection of blocks that go to waste or to the mill, is made. On the basis of sampling results the mine operator will send ore above 3.5 g/t to the mill but not all the ‘ore’ contains more than 3.5 g/t of gold. Because of inaccuracies inherent in sampling some of the ore will contain much less than the desired cut-off grade. Likewise, not all waste delivered to the dump contains less than 3.5 g/t. Some will contain more. Misclassification is a result of the errors introduced by variability during the sampling process. If a normal distribution of classification probabilities is assumed around the cut-off grade, with a standard error of 15%, the effect on the value of the ore blocks could be considerable. Total sampling error significantly affects the value assigned to a mined block of ore. The optimum economic model would be to classify, with precision and accuracy, all the rock below the cut-off grade as waste and all that above the cut-off grade as ore. In such cases all rock would be correctly classified—waste to the waste dump, and ore to the mill. However, the possibility of incorrectly classifying the rock still exists, particularly when the average grade is near the cut-off grade. The influence of poor sampling on the value of the mining operation is therefore related to the distribution of sampling errors in the assay values assumed to be normally distributed.

In panel (c) of Figure 8, the grade control on the 400 t blocks is based on a 100 t sample selected from the top left-hand quadrant of each 400 t block, as shown in panel (a). As can be seen, the result based on such a selection procedure is that two blocks that should have gone to the mill end up on the waste dump, and only one block (whose grade is overestimated) is sent to the mill. In fact the metal sent to the waste dump is twice that sent to the mill, creating a clear case for two interventions, firstly the establishment of low grade stockpiles wherever possible, and secondly regular sampling of the waste dump. The fact that numerous small contractors can make money out of old ‘waste dumps’ scattered across the Wits gold mining landscape is telling. Clearly greater sampling density would provide more information, but it would also cost more. Hence, insight into the variability in grade across an orebody is directly related to the sampling density.

The size of the SMU can vary depending on the type of commodity being mined and may range form 5 x 5 x 10 m blocks to 30 x 30 x 10 m in size. SMUs tend to be larger in mines with lower ‘between-block’ variances, i.e. in
commodities such as coal, and the non-ferrous metals, manganese, iron ore and chromite the variability in grade between SMUs tends to be small. The magnitude of block variances is a direct function of the block size or volume; increasing the sampling density allows the planner to reduce the block size. The mean grade within the area being evaluated remains the same, but ‘within-block’ variances increases exponentially as the drill spacing is reduced and the block size becomes smaller (Figure 9). This means a refinement in the selectivity of blocks that go to the mill or to the waste dump because the volume of selection is smaller.

In Figure 10, which represents the floor of an open pit operation, information is derived from four different sources. The first source is the point source information on grade distribution from exploration boreholes prior to the commencement of mining, the second is information from bench blastholes once the mine is operating, the third is the average grade of SMUs provided by the evaluation team, and the fourth is the average grade of the whole mining bench, information which can only be obtained once the bench is completely mined out. The statistical distributions of three of the different support volumes are shown in Figure 11. Each source of information has an identical average, but the variance of each source is quite different because the support volume for each changes for each level of information. For widely spaced information such as exploration data, the variability is smaller than for the much finer grid spacing used in ore grade control; as the spacing between sample points decreases, the variability also increases.

This example illustrates that errors of judgement incurred because of a lack of information can lead to wrong decisions concerning discrimination between ore and waste simply because the model used is an inadequate picture of reality. There are many cases of mines that have opened only to find there is insufficient ore to justify the operation; and millions of rands are lost. Similarly, many prospects abandoned as uneconomical have been later found (usually by other companies) to be highly profitable.

However, the economics of information (Figure 12) also tells us the importance of keeping in mind that there is an optimal point at which the marginal gains in information through additional drilling are just not worth the extra cost.

**Imposing a cut-off grade**

Imposing a cut-off grade on an orebody means that the SMUs comprising the orebody for a specified mining method, will be classified as ore or waste. The effect of misclassification of SMUs as either ore or waste can have a major impact on

![Figure 10](image)

_A mining bench showing the different support units including points (v) (drillholes), SMUs (v) and full scale benches (V)_

![Figure 11](image)

_Different support volumes with the same mean grade but very different variability_
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The ellipse shown in Figure 13 encloses paired drill hole, chip or face sampling results with the contained metal in blocks or SMUs from a copper mining operation and it illustrates the problem of misclassification well (Pitard, 2006). Although the diagram was established for a copper mine the principles hold true for any operation where there is a large difference in volume between the sample size and the size of the SMU or block being evaluated. For very rich gold mines, where the average grade is very high, imposing a cut-off may be unnecessary, but the application of cut-off grades can make the difference between success and failure for some mining operations. However, we would do well to consider the implications and the outcomes of such an action. The effect of imposing a cut-off grade means that the grade distribution of mineralized rock is truncated.

Choosing a cut-off grade can be complex problem that involves technical and economic considerations, the mining method, the scale of the mining operation, the size of equipment used in mining selection, the ability to define the cut-off boundaries, and physical constraints on access.

Selectivity is a function of variability. The greater the variability the greater selectivity required and greater selectivity usually means greater mining costs. It should also mean that higher grade ore is delivered to the mill which translates into greater revenues. While selectivity is a function of mining method and economics, optimal mining means we must find the balance between geological, technical and economic factors of selection.

In a more local example the Navachab gold mine in Namibia (Figure 14) uses 5 m x 5 m blast holes on 2.5 m high benches, giving an average block volume of 62.5 m$^3$ which at a density of 2.9 kg/t, means that each ore block contains ~180 t. At an average grade of 5 g/t the metal contained in one SMU would be about 900 g of gold which at a price of R135/g means that the value of such a block is about R122 000. Thus the mine could easily lose this amount through a simple decision to classify that particular block as waste material and send it to the waste dump rather than the gold being recovered in the mill. Thus, the cost associated...
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Figure 14—A blast at the Navachab gold mine, Namibia

Figure 15—Implementation of standards for sampling practice and protocol for mining process efficiency

Estimations based on sparse sampling yield images, which are significantly different from reality
► Estimated images are smoothed versions of reality; the degree of smoothing decreases as the number of samples increases
► Estimated images cannot provide the same level of detail as exists in the true image
► The consequences of making engineering and economic decisions based on poorly estimated images of a mineral deposit can be disastrous.

Conclusions

Poor precision in samples generates huge ore grade misclassification. This is compounded by the desire of management to apply overselective ore grade cut-offs and feed the mill with ore at an average grade that was determined during the feasibility study. The effects of random variability are such that misclassification of ore can occur, the higher the cut-off grade the greater is the opportunity for misclassification. When the expected grade is not obtained, management may be tempted to increase the gold grade cut-off. Such reactive decisions drastically reduce the ore reserves and generate much more waste than anticipated. The model on which further decision making is going to be based must be fit for use, and overspending to obtain irrelevant detail should be avoided. The general conclusions that can be drawn are:

➤ Implement sampling code and guidelines for best practice in regard to sampling in the minerals industry. (Review ISO Standards wrt Theory of Sampling and standards application)
➤ SAMREC code and JSE Listing rules provide clear definition of sampling procedures, practices and QA/QC requirements

Management awareness of hidden costs at individual company level and individual mining operations. QA/QC accountability to management.

Improved understanding of the importance of sampling in the minerals industry. Short courses, training and workshops on Theory of Sampling
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Pitard (2006) was the first to suggest that standardization through the identification of structural problems and continuous improvement of mining processes be instituted at a national level. This would ensure that standards for best practice, training of personnel at the highest levels and a strongly developed sense of accountability will mean that investors' interests are protected and that the nations mineral wealth is optimally developed and exploited.

The South Africa mining industry itself should be the first custodian of the primary interest for optimal exploitation of the national mineral assets. With the transfer of mineral rights ownership from private to public hands, the primary responsibility for optimal mineral exploitation also now vests with public institutions. Thus the DME is the primary custodian of the first interest in optimal exploitation as suggested in Figure 15. Furthermore it is implied in the progression of actions to be taken, as shown in Figure 15, that the statutory professional bodies take responsibility for setting up national working groups to address the structural problems facing the mining industry. Such an initiative was spearheaded by the SAMREC Working Group under the auspices of the SAIMM, and has succeeded in producing for the minerals industry a world-class document for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves. Of particular note would be the importance of training, presentation of short courses by world experts, and workshops to strengthen the knowledge base and improve skills. Amongst other things, QA/QC accountability and an improved awareness of management of the losses incurred because of poor sampling protocol and practices would be beneficial. A similar initiative to develop a set of guidelines and a code for sampling practice would serve our minerals industry well.

References


Pitard, F.F. Sampling Theory and Practice. A Short Course presented through the Geostatistical Association of Southern Africa, at the University of the Witwatersrand, October 2006.

