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The value of automated mineralogy

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ABSTRACT

Automated mineralogy methods and tools, such as the Mineral Liberation Analyser (MLA) and the QEMSCAN, are now widely used for ore characterization, process design and process optimization. Several case studies published recently demonstrate that large gains can be obtained through grinding and flotation optimization guided by automated mineralogy data. However, since automated mineralogy can only provide the information pointing to where the process gains can be made, it does not directly impact the production gain. Thus the question is often asked: how to value the contribution of automated mineralogy to process improvement at a particular plant. This appears to be a difficult question to answer. On close examination however, it is found that this is essentially a question of the value of information and this is reasonably well documented in various other industries. Hubbard, 2010, in chapter 7 "Measuring the Value of Information", dealt with exactly this type of problem. The value of information is the reduced risk of an investment and opportunity loss. The methods Hubbard developed can be applied to estimate the value of automated mineralogy, as well as metallurgical test work, both producing information that reduces the risk of investment.This paper first introduces Hubbard's theory on the value of information and how to measure it. It then applies his methods to estimate the value of automated mineralogy, using Anglo Platinum's fine grinding project as an example. In the end, a general model is developed to allow the simulation of the value of automated mineralogy in different mining operations constrained by different parameters.

1. Introduction

Automated mineralogy methods and tools, such as the Mineral Liberation Analyser (MLA) and the QEMSCAN, are now widely used in the mining industry worldwide, with close to two hundred of these systems installed in research and company central labs over the last ten years. By measuring samples of ore and processing plant material, these instruments provide statistical distribution of the size distribution and associations of minerals of interest, critical for ore characterisation, process design and optimization. As such, automated mineralogy has become an important contributor to process mineralogy and geometallurgy. Several case studies of the application of automated mineralogy for process improvements were published recently (Rule and Schouwstra, 2011; Rule, 2011; MacDonald et al., 2011; Lotter, 2011; Lotter et al., 2010), demonstrating significant returns obtainable through grinding and flotation optimisation supported by automated mineralogy data.

It must be emphasized that automated mineralogy can only provide information pointing to where the process gains can be made and the extent of the benefit. To realise the gain, the processing plant needs to be adjusted and, in most cases, modified significantly by expert process engineers. Consequently, the link between automated mineralogy data and final production gain is indirect. As such, the question is often asked how to value the contribution of automated mineralogy to process improvements at a particular plant.

The answer to the above question is of interest for at least three reasons. Firstly, a proper valuation of automated mineralogy information will assist managers to determine the level of investment considered necessary to obtain such information, giving the size of the mine and operation. Secondly, it will guide the automated mineralogy profession to produce higher value and more relevant information. Thirdly, it will encourage the evaluation of process improvement proposals, therefore reducing the risk and maximising the return of mining investment.

So far, there are only qualitative statements in the literature regarding the value of automated mineralogy. Quantitative mineralogical data are often used as a diagnostic tool to pin point the

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problem area or unit in a processing plant. There are a number of case studies showing significant returns from optimising plant operation or plant design based on that information (Lotter 2011). Quantitative measurement of the value of automated mineralogy has not been studied to date. On the surface, it appears to be a difficult subject and vexing problem to solve. However, it is essentially a question of the value of information, which is reasonably well documented in various other industries. Hubbard (2010), in chapter 7 "Measuring the Value of Information", dealt with exactly this problem and provided a good framework which can be used to estimate the value of automated mineralogy.

This paper introduces Hubbard's theory in the context of mining industry and applies it to estimate the value of automated mineralogy, using Anglo Platinum's fine grinding project as an example. Afterwards, a general model is developed to allow the simulation of the value of automated mineralogy in different mining operations constrained by different parameters.

2. Measuring the value of information – Hubbard's theory

2.1. Measurement and "intangibles"

Measurement is "A quantitatively expressed reduction of uncertainty based on one or more observation" (Hubbard, 2010, p. 23). It never completely removes uncertainty. Based on this definition, many of the things that were thought to be impossible turned out to be quite easy to measure. Hubbard (2010, p. 4) observed "Intangibles that appear to be completely intractable can be measured. This measurement can be done in a way that is economically justified." For many organisations, it is a routine task to measure the risk of bankruptcy, the value of public health initiatives and the value of IT investments. Through many case studies, Hubbard found that the perceived impossibility of measurement is often an illusion caused by not understanding:

1. The *concept* of measurement – reduce uncertainty and hence risk.
2. The *object* of measurement – the core of the question and the purpose.
3. The *methods* of measurement – model the uncertainty statistically.

Once those aspects of a problem are clearly defined and understood, then the question becomes how to best measure it. He proposed the following general approach:

1. Model what you know now.
2. Compute the value of additional information.
3. If economically justified, conduct observations that reduce uncertainty.
4. Update the model and optimise the decision.

2.2. Measure the value of information

"Information reduces uncertainty about decisions that have economic consequences". In other words, "Information can reduce the uncertainty. Reduced uncertainty improves decisions. Improved decisions have observable consequences with measurable value." It is generally recognised that information has value, but how to measure the value of information is not generally known.

If we can estimate the "chance of being wrong and the cost of being wrong" about a decision, then their multiplication is "Expected Opportunity Loss" (EOL). The Expected Value of Information (EVI) is simply the reduction of EOL after information and EOL before information available.

Once we know the value of information, we can use that to determine how much we should spend to obtain that information (Hubbard, 2010).

The above are the essentials of Hubbard's theory and methods that are relevant to this paper. It will become clearer when we apply them to derive an effective method for measuring the value of automated mineralogy.

3. A case study – Anglo Platinum's fine grinding project

Anglo Platinum, the world's largest primary producer of platinum, has invested substantial capital to build the capacity to track the mineralogy of processing plants and ore sources. After a detailed study into the losses of value minerals (platinum group minerals and sulphides) it became clear that to improve recoveries an increase in liberation of the value minerals would be required. After some pilot testing to demonstrate that finer grinding would increase the liberation and recovery of the value minerals a decision was made to go ahead with large scale implementation of a fine grinding project in 2009. The outcomes of the implementation of fine grinding at the Amandelbult operation were published in detail in Rule (2011) and Rule and Schouwstra (2011). In summary, the Amandelbult project resulted in 50% reduction in tailings grade with corresponding increase in recovery of over 5% of platinum group of metals (PGM). If an improvement in recovery of 1% in PGM could be implemented across all the operations in the group this would translate into a gain in excess of US$75 million annually for Anglo Platinum (2009 estimates based on annual production, PGE prices and exchange rate, Rule and Schouwstra, 2011). The capital cost of implementing the fine grinding program is US$250 million and annual running cost of the additional grinding equipment is US$15 million. Based on these estimates the return of capital investment for this initiative is within six years and the net present value (NPV) of this project is approximately US$158 million based on annual discount rate of 10% for 12 years.

This is a good example to demonstrate how to measure the value of automated mineralogy using Hubbard's method. The NPV of US$158 million is attributed to automated mineralogy and metallurgical test work carried out before and during the implementation of the fine grinding project. The cost of the automated mineralogy and metallurgical test work totalled to less than US$2 million/annum, an insignificant amount compared to the value gained.

The value of automated mineralogy is to provide information that reduces the risk of fine grinding project:

1. By estimating the potential gains of the project, which effects the decision on how much to invest in the fine grinding project.
2. By helping the metallurgists to determine how fine to grind and to optimise the circuit design.

Let us assume that at the time when Anglo Platinum considered the fine grinding project, management believed the investment should have a good chance of success (say 80% of the target). This estimation is based on available automated mineralogy information and preliminary pilot test work. Let us further assume that without the automated mineralogy information, the estimated chance of success would be 55%. This and relevant information are listed in Table 1.

So, from the investment point of view, automated mineralogy reduced the risk from 45% to 20%. Since we are investing US$250 million, the expected value of information (EVI) is US$62.5 million = $250 \times (0.45 - 0.20)$. From potential gain point of view, automated mineralogy reduced the risk of this project being rejected. The EVI is US$39.7 million = $158 \times (0.8 - 0.55)$.