

Utilizing a Value of Information Framework to Improve Ore Collection and Classification Procedures

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November 2008

Abstract:

This case study utilizes a value of information decision framework to provide mine managers guidance regarding the purchase of ore grade scanners. LKAB's Kiruna mine produces three types of iron ore to meet long-term contractual agreements on a monthly basis. There is *a priori* uncertainty regarding the ore type in any given mineable section of the orebody. In addition, there is extracted ore type uncertainty which is introduced by the mining process. These uncertainties are better understood by obtaining more precise (real-time) information. In addition, a better understanding of the uncertainties can improve the quality of operational decisions and increase the overall profitability of the mine. This case study provides a framework for measuring the economic impact of information purchases in a mining context and discusses the implications of those findings.

Introduction

Economic decision analysis models provide a robust framework for understanding complex problems and improving the quality of decision making under uncertainty. Economic decision analysis can provide a foundation to support strategic investment and operational decisions, particularly when they are characterized by significant uncertainty. In this case study, we implement a value of information methodology to analyze a mine company’s decision to purchase ore grade scanners. We demonstrate that the expected financial benefits of installing ore grade scanners far outweighs the costs. In addition, the scanner purchase enables the world’s largest underground iron ore mine to better meet long-term contractual agreements.

The Loussavaara-Kiirunavarra Aktiebolag (LKAB) company operates an underground iron ore mine north of the Arctic Circle in Kiruna, Sweden. The mine produces three ore types, each with different processing requirements and monthly production targets. Kiruna’s mining method, sublevel caving, leads to a high degree of ore dilution during recovery, which, in turn, creates significant uncertainty in the quality of the extracted ore. We evaluate an ore grade scanner technology that provides information that may improve the quality of mine operators’ decisions with respect to ore type identification and subsequent classification. We utilize a value of information framework that can potentially enable a decision maker to make better choices in the context of the underlying uncertainties. The results of our work yield the following benefits: (i) a methodology for estimating the costs associated with ore misclassification errors in the mining sector; (ii) a real-world application of the value of information framework as it relates to the mining sector; and (iii) a prescriptive approach to improving operating decisions in mineral production.

This paper is organized as follows: first, we review the relevant literature. Then, we discuss the issue of ore misclassification and identify the causes and magnitude of misclassification errors over a three-year period using ore extraction data obtained directly from the company. Next, we approximate the cost of these misclassification errors to the Kiruna mine. We then use a value of information framework to analyze the impact on decision making of obtaining additional information on extracted ore quality. We compare the expected value of additional information to the cost of purchasing the source of information. We conclude with a summary of our findings and the managerial implications.

Literature Review

A variety of deterministic and stochastic decision models have been applied to complex problems in the mining sector. Deterministic models, e.g., static net present value calculations, compare costs and benefits of alternative mining methods given assumptions regarding orebody size and shape, reserve quantity and quality, and market prices (Boshkov and Wright, 1973). Laubscher (1981) outlines factors affecting underground mining method selection including regional rock stresses, rock mass classification, and location and layout of orebody geometry. Sevim and Sharma (1991) select least-cost transportation options for surface coal mines. Nicholas (1981, 1992) ranks different mining methods based on a set of critical decision factors and then performs a cost analysis on the highest-ranked methods to determine a least-cost implementation. Çelebi (1998) uses an integer program to select the optimal mix of equipment to strip Turkish surface mines.

Stochastic modeling methods have also been utilized in the mining sector as a means to support decision making. Kappas and Yegulalp (1991) use queuing theory to analyze a truck and shovel system in an open pit mine to determine optimal operating and dispatching policies. Zhonghou and Qining (1988) use a

similar methodology to select trucks and shovels for mining operations. Dimitrakopoulos et al. (2002) apply uncertainty and risk analysis in open-pit design and production scheduling. Magalhães et al. (1996) utilize simulation techniques to set operational policies for trains in underground mines. Sturgul (1996) provides a comprehensive review of mine simulation literature.

Our emphasis in this work is on the application of a decision science approach known as value of information (VOI) methodology. Previous applications of this stochastic approach to support decision making are limited in the mining sector. Peck and Gray (1999) make no explicit reference to VOI, yet they discuss the potential benefits to decision makers of gathering information in the mining industry. Barnes (1986) uses VOI to incorporate geostatistical estimation into mine planning. Typical estimates done via kriging provide not only a parameter estimate, but also a measure of the uncertainty associated with this parameter, the parameter variance. The author investigates geologic delineation sampling as a technology that has a cost and information value associated with it.

In comparison to the mining sector, the value of information approach has been researched more extensively in a related industrial sector - the oil and gas industry. Grayson (1960) was first to demonstrate the application of VOI to information purchases that may aid drilling decisions. Newendorp (1975) also discusses value of information in his classic petroleum decision analysis text. More recently, there have been a number of illustrations and applications of value of information applied to seismic information purchases. Seismic data represent an essential source of information utilized to characterize geological and/or geophysical features and to assist in hydrocarbon reservoir characterization and management. Seismic data can have significant economic benefit and cost implications. Much of the previous research and many of the applications of VOI techniques in the oil and gas sector focus on the value of seismic information. For a more extensive literature review of the theory and application of value of information concepts in the oil and gas industry, see Bratvold and Bickel (2007). Other works include the examination of the accuracy of that information (Stibolt and Lehman, 1993; Houck, 2004; Steagall et al., 2005; Pickering and Bickel, 2006). The issue of information accuracy and its impact on the value of information is an important element of our work which concerns ore collection and classification procedures.

This research advances the use of economic decision analysis methodologies (VOI) as they apply to the mining sector. This work contributes to the economic decision analysis literature by: (i) providing a sound and practical technique for the application of the value of information approach in a complex mining decision context; (ii) informing the academic community about the practice of economic decision analysis in the mining sector; and (iii) describing an actual application with demonstrable value to the participating organization.

The Kiruna Mine and Ore Misclassification

The Kiruna orebody is a high-grade magnetite iron ore deposit approximately four kilometers long and 80 kilometers wide (Kuchta, 2002). Mine operators extract the iron ore via a mass mining method known as sublevel caving which employs the concept of gravity flow to assist in ore recovery. Drifts are drilled horizontally into the orebody and then charged and blasted, which causes the ore to filter down into the drift. After a drift is blasted, load haul dump units transport the ore to an orepass. Ore from an orepass fills a 455-ton capacity train on the main haulage level. The train then transports the ore to a set of four

crushers, three of which are operational at any point in time. After the ore is crushed, it is hoisted to the surface and is processed at one of four mills before the product is shipped to markets (steel mills) in Europe and the Middle East. Figure 1 depicts a typical sublevel caving operation.

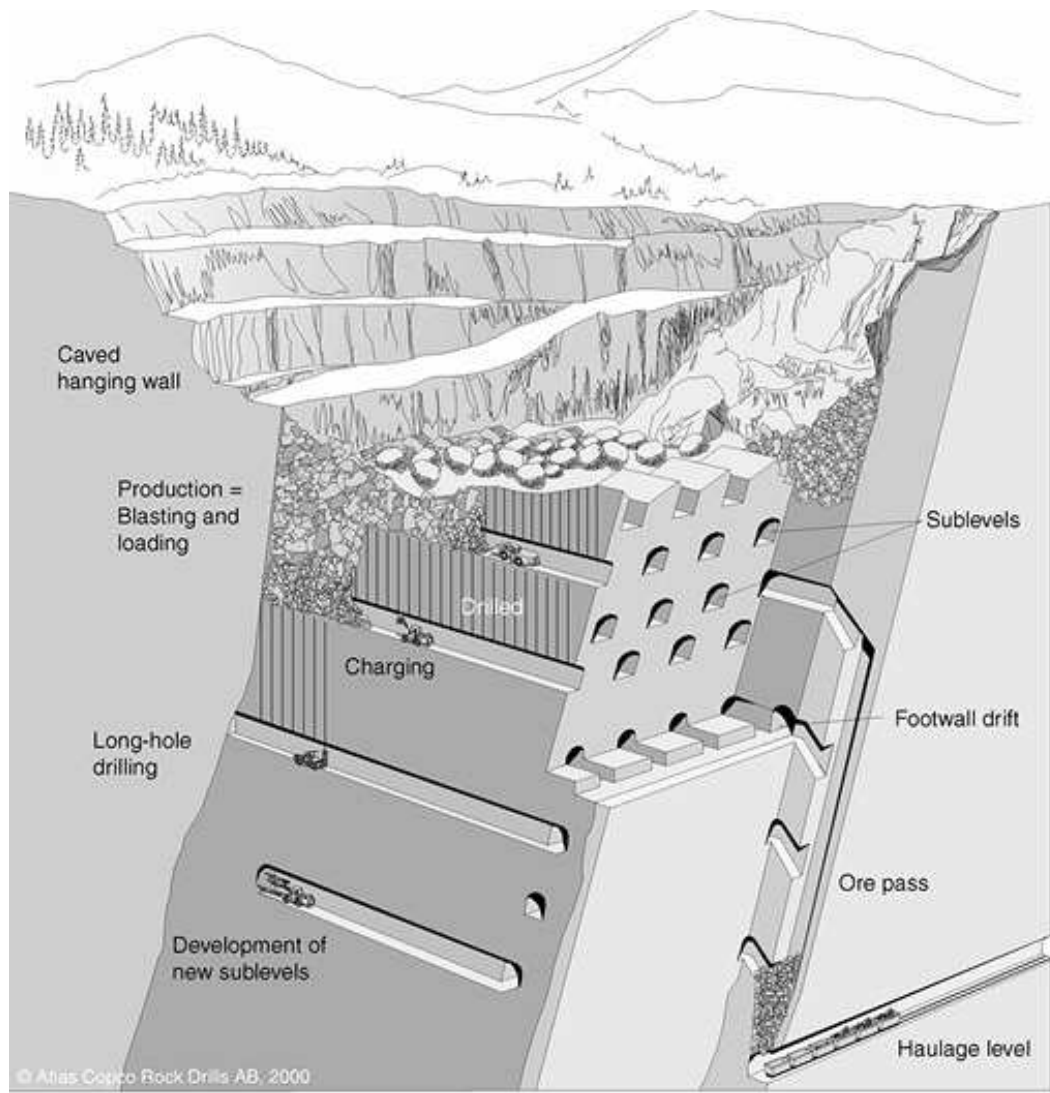


Figure 1: Representation of sublevel caving (www.atlascopco.com)

Extracted Ore Grade and Ore Grade Uncertainty

There are two main ore types located *in situ*. About 80% of the orebody contains a high iron, low phosphorus *B* type ore and the remaining 20% is a high phosphorus *D* type ore. Extraction of the two *in situ* ore types yields three ore types that are then processed: *B1*, *B2*, and *D3*. *B1* ore is characterized by having a high iron content ($\sim 68\%$ on average), a low phosphorus (*P*) level ($\sim 0.06\%$), and a potassium (K_2O) level lower than 0.15% . Raw *B1* ore is enriched simply by crushing and grinding it to a small particle size, and then using magnetic separation to obtain the ore (fines), leaving the impurities behind. Although this processing method is relatively cheap, the product cannot be ground to too fine a granularity, because it

would become too difficult to handle. (One can handle sand, but not dust.) However, the coarser granularity of the final product limits the degree to which the impurities can be removed. Hence, ore classified as *B1* can contain only limited amounts of the two impurities found at Kiruna, *P* and K_2O . *B2* ore is typically formed during the extraction process when the high iron content, low phosphorus content *B1* ore mixes with waste rock, raising the phosphorus content of the ore. On average, the *B2* ore contains approximately 0.2% *P*, but the K_2O level is irrelevant. Raw *B2* ore is enriched in much the same way that *B1* ore is, only the ore is ground to a much smaller particle size. The smaller size allows a higher level of impurities to be extracted via magnetic separation, but the resulting product, of the consistency of dust, is difficult to handle and must be transformed (at an expense) into pellets suitable for transportation. *D3* ore has the highest level of phosphorus, greater than 0.9% *P* (Topal, 2003). Raw *D3* ore is also crushed and ground, but a more expensive flotation process is used to remove all contaminants, regardless of their levels. Table 1 illustrates the average content of the key elements. Note that phosphorus is the primary distinguishing factor. Potassium content is important only when categorizing *B1* ore.

Table 1: Characteristics of the Three Ore Types (Topal, 2003)

Ore Type	%P	%K ₂ O
B1	0.06	0.15
B2	0.2	-
D3	0.9	-

Because the geological samples are not perfectly accurate, there is *a priori* uncertainty regarding the ore type in any given mineable section of the orebody. In addition, there is extracted ore type uncertainty which is introduced by the sublevel caving mining method, which has the major disadvantage of a high amount of ore dilution that occurs during recovery. Initially, most of the blasted material consists of ore. However, later in the recovery process, gravity causes waste rock to filter down to the recovery area and to mix with the ore, and the levels of waste rock recovered start to rise. At a predetermined level of dilution (i.e., when a load collected from a drift contains 50% ore and 50% waste), recovery from the drift is complete. Although mine operators can visually estimate the level of dilution, it is difficult to accurately predict because of the complexity of the gravity flow process.

Each orepass is designated to collect a specific type of ore and each crusher processes a certain ore type which is then transferred to the mill. Because there is no ore reclassification between the crusher and the mill, we use either the term “crusher” (while the ore is in the mine) or “mill” (after the ore leaves the mine) to refer to the destination of interest. It is critical to keep the ore in each orepass and in each crusher homogeneous to avoid ore contamination which could change the classification of the ore and affect the mine’s ability to meet its production targets. The ore is sampled at the crusher and an assay is conducted by lab technicians who analyze the specimen to determine the chemical content of the ore, specifically, the phosphorous content. The assay of the ore at the crusher is the first time the composition of the extracted ore is realized after the ore is deposited into a crusher. If the results of this assay reveal a different ore type than mine operators anticipate from a particular shaft, the result is a misclassification error.

Ore Misclassification

Kiruna provided a data file that contains every recorded ore extraction event from September 2001 to June 2004, totaling 123,123 observations. We obtained the data directly from the company and used them without any modifications. Variables in this data file include: load number, date and time of load dumping, weight of the ore load, crusher number, crusher ore classification ($B1$, $B2$, or $D3$), the shaft from which the ore was collected and the shaft's ore classification, and the assay information from each ore load. We use these data to identify not only the existence of a misclassification error, but the number of misclassifications of each type that occurs.

We define a misclassification error as: a load of ore of a certain type (e.g., $B1$) that is dumped into a crusher meant to process a different ore type (e.g., $B2$). There are two types of misclassification errors that we can identify from the data set and for which we hope to correct:

1. E_L : An incorrectly dumped ore load due to a lag in shaft reclassification
2. E_A : An incorrectly dumped ore load due to fixing the overall moving average of $\%P$ and, if applicable, $\%K_2O$ in each ore type

Error Due to a Lag in Shaft Reclassification (E_L)

After a train collects an ore load from an orepass, that load is then deposited into a crusher. As the ore is dumped into the crusher, an assay is taken to determine the type of ore collected based on its chemical properties. The assay represents a 100% accurate measure of the ore grade composition and eliminates any uncertainty about ore grade at that point in the mining process. If the results of the assay reveal that the actual ore type from a particular shaft is different than the anticipated ore grade, i.e., the ore grade that is determined *a priori* through geological sampling techniques, a misclassification error has occurred because the ore cannot be reclassified in the crusher. We assume that only one ore load is misclassified until mine operators change the shaft classification in the computer system.

Error due to Fixing Moving Averages (E_A)

As each train load of ore is processed, the mine updates the averages of the $\%P$ and $\%K_2O$ in each crusher. In order to maintain these averages within tolerance limits (see Table 1), it is sometimes necessary to redirect one ore type to a crusher that processes another ore type. For example, suppose the moving average of $\%K_2O$ in processed $B1$ ore exactly matches the maximum tolerable level for $B1$ ($\sim 0.15\%$). Based on assay information obtained from the last train load from a specific shaft, mine operators anticipate that the next train load of $B1$ ore from that shaft has a higher than average $\%K_2O$ content, which, if deposited in the $B1$ crusher, would drive the current running average of $\%K_2O$ for $B1$ ore beyond the acceptable limits. Therefore, the next load of $B1$ ore is intentionally dumped into the $B2$ crusher. We refer to this as an error due to fixing moving averages, E_A .

Testing for Error Correlation

Every time a load of ore is deposited into the wrong crusher, because of the uncertainty surrounding the ore type in the shaft, the average $\%P$ and/or $\%K_2O$ of the ore in the crusher can be driven outside of

maximum tolerable levels. In order to correct this, mine operators may have to purposefully misclassify ore to bring the averages back within tolerance levels. In other words, in order to correct for an occurrence of E_L , mine operators may have to intentionally create an occurrence of E_A . Suspecting that there exists a degree of correlation between E_L and E_A , we use SAS (SAS Institute Inc., Version 9.1) to run a correlation analysis between the occurrences of both error types. However, we find less than 3% of the observations exhibit correlation between E_L and E_A . Because of the lack of correlation between operational activities, we did not pursue the nature of the correlation, i.e., linear or nonlinear. And therefore, in our subsequent analysis, we can determine the effect of each error on the cost of ore misclassification independently, i.e., without confounding effects. Had there been significant positive correlation between error types, we would have had to have determined the nature of the correlation and then treated only one of the error types in our analysis of the benefits of correcting for the error. Our analysis would have then yielded a lower bound on the benefit.

Summary of Prior Probabilities

For our analysis, we compute the probability that the ore deposited in a particular crusher is $B1$, $B2$, or $D3$ given it is anticipated to be one of these three types. In other words, we compute the entire matrix of prior probabilities. Not surprisingly, the probability the ore is the anticipated type is greatest for each ore type. However, there is some probability in all cases that the ore is misclassified, i.e., thought to be a type other than what it actually is. This misclassification occurs due to either E_L or E_A . We summarize these statistics in Table 2.

Table 2: Percentages of anticipated versus actual ore type.

Anticipated	Actual B1	Actual B2	Actual D3
B1	84.3%	11.5%	4.2%
B2	11.2%	77.8%	11.0%
D3	2.5%	9.3%	88.2%

Implications of Errors

We use the misclassification errors to compare the amount of each ore type the mine produced to the amount the mine could have produced in the absence of misclassification errors. We refer to these two quantities as actual and estimated ore production, respectively. Additionally, we use the concept of anticipated production to refer to *a priori* estimates of each ore type contained in the orebody. Specifically:

- *Actual Type k Ore Production*: All ore deposited into the ore type k crusher as measured by the assay
- *Estimated Type k Ore Production*: All ore correctly deposited into the ore type k crusher *and* all type k ore incorrectly deposited into crushers that contain ore other than type k
- *Anticipated Type k Ore Production*: All ore in a certain section of the orebody determined *a priori* through geological sampling techniques to be ore type k

We also use the term *expected* ore type in the conventional sense in the value of information framework where we employ decision analysis techniques. Figure 2 compares the actual and estimated ore production for *B1* ore against monthly production targets.

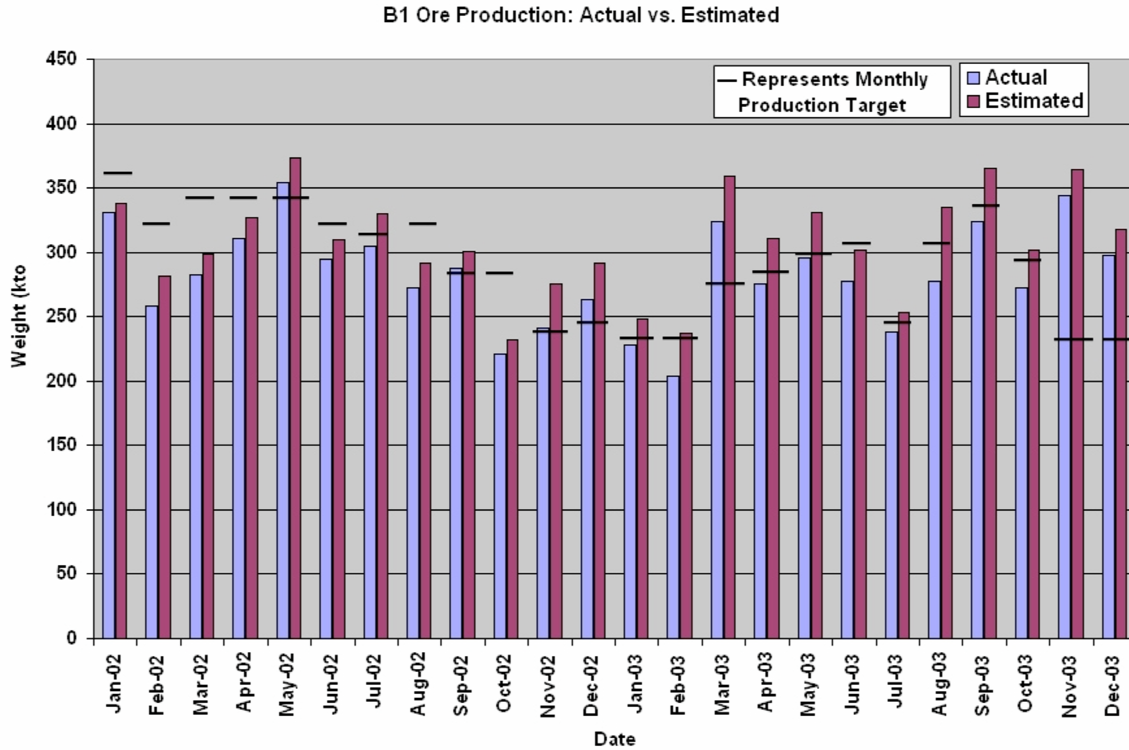


Figure 2: **Actual Ore Production vs. Estimated Ore Production and Monthly Production Targets for B1 Type Ore:** The two bars for each month represent the amount of each ore type the mine produced (actual) and the amount the mine could have produced in the absence of misclassification errors (estimated). The dashes represent Kiruna’s monthly production targets.

In the absence of misclassification errors, more *B1* ore could have been produced each month, thus decreasing the shortfall in *B1* ore production. Our research analyzes solely the benefits of using a value of information framework to improve collection and classification for the *B1* ore type. This ore type is the purest one mined at Kiruna, thus making meeting production targets for *B1* ore the most difficult. We could use the same analysis techniques to draw conclusions regarding *B2* and *D3* collection and classification procedures because comparisons between actual and estimated ore production for *B2* and *D3* ore reveal errors as well. That is, sometimes *B2* ore is underproduced and *D3* ore is always overproduced.

The Cost of Ore Misclassification

We consider the cost of ore misclassification to consist of the resulting profits foregone. There are other, difficult-to-quantify cost factors such as the opportunity cost of freight ships waiting for ore from the mills and customer dissatisfaction due to delayed shipments. We consider the latter cost to be inconsequential for our study because of the long-term nature of the ore contracts. Despite our exclusion of these other costs, our estimate of the cost of ore misclassification is valid because it is a lower bound on the actual cost. That is, the misclassification cost is at least as high as we estimate.

To collect actual costs of ore misclassification, we use the World Mine Cost Data Exchange (WMCDE, 2005), an internet-based resource that provides a cost database and comprehensive cost models for the world's major metal markets. From this database, we obtain profits, ore prices and detailed operating costs at the Kiruna mine and at its mills. We use this database to determine the costs of mining and milling each ore type and the historical selling price for each ore type.

In calculating the profits foregone, we ignore any profits that might be made by selling the misclassified ore as a different ore type (and, correspondingly, any costs associated with processing the ore into a type other than what it was anticipated to be) because we assume that there is no spot market for any ore produced over the mine's target. The profits foregone are the product of (i) the margin (the price of the ore less the cost of the ore production) and (ii) the average amount of ore in a train load arriving at the crusher. Letting:

- a : number of tons in an average train load (tons per train)
- c_i^1 : mine cost for ore type i (\$ per ton)
- c_i^2 : mill cost for ore type i (\$ per ton)
- p_i : price for ore type i (\$ per ton)
- m_{ij} : margin for ore type i sent to mill j (\$ per ton)

the calculation for profits foregone per trainload of ore is given in Equation (1) below.

$$\text{Profits Foregone}_{ij} = m_{ij} * a \tag{1}$$

$$m_{ij} = \begin{cases} p_i - (c_i^1 + c_i^2), & \text{ord}(i) \neq \text{ord}(j) \\ 0, & \text{ord}(i) = \text{ord}(j) \end{cases}$$

$$\forall i \in \{B1, B2, D3\}, \quad j \in \{B1 \text{ Mill}, B2 \text{ Mill}, D3 \text{ Mill}\}$$

The $\text{ord}()$ function denotes the ordinal position of an element in a set. We give the profits foregone for each of the nine mill and ore type combinations in Table 3.

Obtaining the cost of ore misclassification is critical for evaluating the decision of whether to purchase technology that could be used to reduce misclassification errors. Specifically, the information from the scanner helps to reduce the occurrence of errors due to a lag in shaft reclassification and due to fixing

Table 3: **Calculation of Profits Foregone (\$/train load)**. Column 1 gives the mill type. Column 2 gives the ore type that is sent to that mill. Column 3 is the margin for the ore type in column two. The fourth column is the product of the average train load size (455 tons) and the margin (column 3).

Mill	Ore Type	Margin (\$/ton)	Profits Foregone (\$/train load)
B1 Mill	B1 Ore	0	0
B1 Mill	B2 Ore	16.52	7,517
B1 Mill	D3 Ore	14.24	6,479
B2 Mill	B1 Ore	4.22	1,920
B2 Mill	B2 Ore	0	0
B2 Mill	D3 Ore	14.24	6,479
D3 Mill	B1 Ore	4.22	1,920
D3 Mill	B2 Ore	16.52	7,517
D3 Mill	D3 Ore	0	0

the moving averages by scanning the extracted ore before it is directed to a specific crusher. We apply the misclassification costs, which we have computed as lower bounds on the actual costs, in a value of information framework used to investigate the economic feasibility of acquiring additional information to help correctly identify ore grade.

Value of Information

Decision makers who face uncertain prospects often gather information with the intention of gaining a better understanding of the key uncertainties. The intuition for gathering information is relatively straightforward. As decision makers, we want to make choices that maximize our objective; in the case of mine managers, that objective is profitability. Additional information about future outcomes may hold the possibility of changing the decision that would be made without further information. The value of information approach enables the manager to make systematic decisions regarding what source of information to select or purchase and how much that particular source of information may be worth.

We use value of information analysis to determine whether or not a scanner technology known as a Laser-Induced Fluorescence (LIF) analyzer is worth purchasing. The benefit of an LIF analyzer is that it would assay the ore before the load haul dump units deposit it into an orepass; this is in contrast to the current practice of waiting until the ore is dumped into the crusher. We compare the expected benefit of additional information regarding ore grade uncertainty obtained through the scanners, hence, reduced ore misclassification, to the purchase price and maintenance costs of the scanner. In this way, we can analyze the question of whether the expected benefits of the scanners are greater than the costs. We use decision trees to characterize uncertainties faced by a decision maker, and to make choices among the available alternatives,

including the purchase of additional information.

Kiruna’s Current Decision

We begin by analyzing the current decision problem regarding ore type uncertainty using as our unit of measure a train load of ore. When the train collects ore from an orepass and travels to the crusher, mine operators assume that the train contains a specific ore type based on the last ore type observed from the same shaft. However, as we show empirically in Table 2, a load dumped into any crusher can be realized as either $B1$, $B2$ or $D3$ ore even though, in this example, because mine operators are extracting ore from a section anticipated to be $B1$ from the geological samples, we anticipate $B1$ ore is contained in the train. Hence, mine operators face uncertainty in ore grade and the choices include into which crusher, $B1$, $B2$, or $D3$, to dump the trainload of ore. Figure 3 represents the base case decision tree with the current decisions and uncertainties mine operators face when a train arrives at the crushers.

Using patterns in the data to determine instances of the misclassification errors, E_L and E_A , we calculate the proportion of time a particular ore type is dumped into a crusher containing a specific ore type (see Table 2). We place the corresponding probabilities in the first row of this table on the uncertainty branches in the decision tree. These values represent the proportion of time that the actual ore type is $B1$, $B2$, or $D3$ given the mine operators anticipate the train to contain $B1$ ore. Specifically, given that a train load is anticipated to carry $B1$ ore, 84.3% of the time the train contains $B1$ ore, 11.5% of the time it contains $B2$ ore and 4.2% of the time it contains $D3$ ore.

For each instance in which mine operators deposit ore into the correct crusher, the cost (profits foregone) of misclassification is zero. If the ore is deposited into an incorrect crusher (e.g., $B1$ ore into the $B2$ or $D3$ crusher), the cost associated with this misclassification follows from Equation (1). Using the probabilities and costs of each outcome, we calculate an expected cost for each decision. For example, given the mine operator chooses to deposit the ore in the $B2$ crusher (assuming $B1$ ore is anticipated), the expected cost for this decision is \$1,891, as shown in the decision tree in Figure 3. We utilize the decision tree to provide guidance on the best alternative given our objective is to minimize the cost of ore misclassification. In Figure 3, the optimal choice is to deposit the anticipated $B1$ ore load into the $B1$ crusher, as it has a minimum expected cost of \$1,137 per train load. This lowest cost alternative is referred to as the best decision alternative without information. Although this result is easy to discern without the use of a decision tree, the decision tree framework is necessary in our subsequent analysis.

Evaluating the Information Alternative

The critical uncertainty in the Kiruna mine operation is the ore grade being transported to the ore pass and ultimately to the crushers. There is an information technology available that may enable mine managers to improve operational decisions with regard to this uncertainty, thereby reducing the high cost of misclassification errors. LIF scanners can measure ore quality in the Kiruna mine. We analyze the value of the LIF’s ability to predict ore grade. We then compare this value to the cost of purchasing and operating these scanners.

We consider the value of *perfect* and *imperfect* information. By perfect information, we mean information that is perfectly reliable - it predicts outcomes correctly 100% of the time and, therefore, resolves uncertainty. Perfect information rarely exists, but, because it provides a best-case scenario for the value of an information

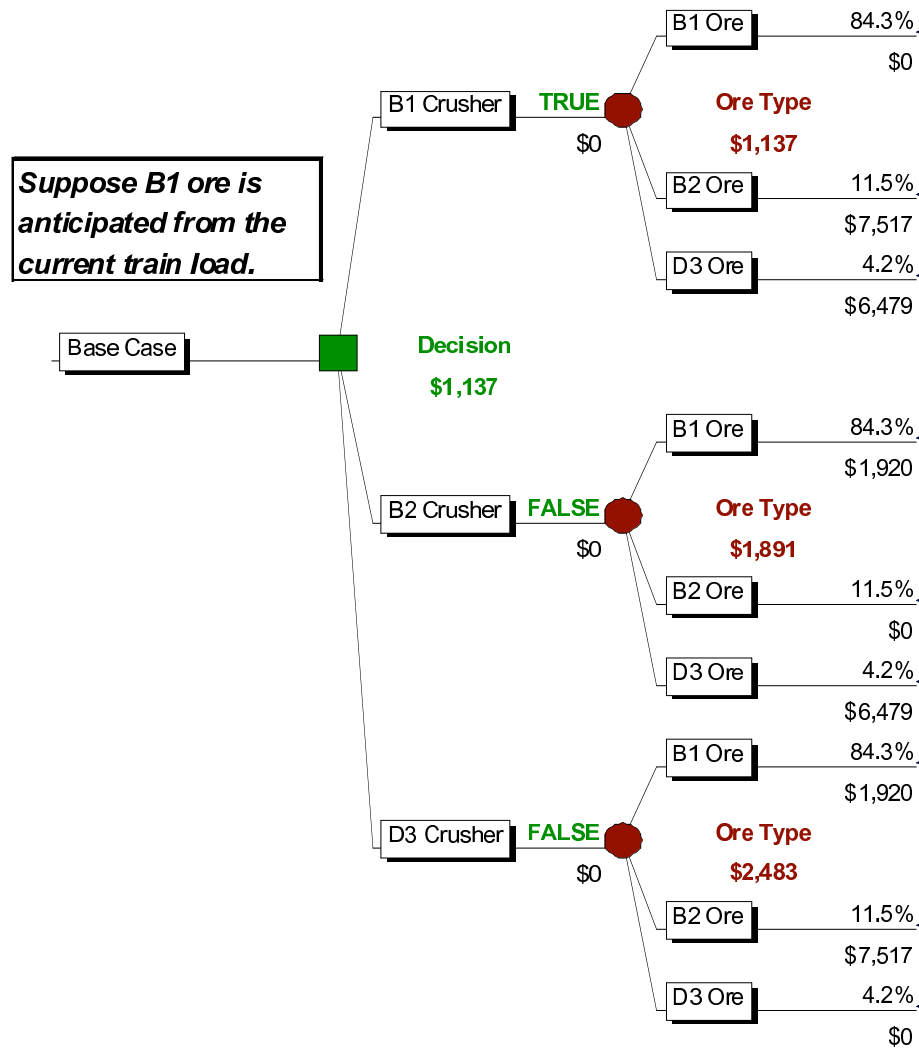


Figure 3: **Base Case Decision Tree.** This decision tree depicts the decisions and uncertainties associated with a trainload of ore arriving at the crushers. The costs (profits foregone) on each branch are the costs reported in Table 3.

source, it yields an upper bound on the value of additional information. In other words, it answers the question: “How much better off would I be right now if I could make a decision after knowing what outcome will occur?”

Figure 4 shows the decision tree analysis of the perfect information problem assuming the availability of a perfect information source regarding ore grade. The top branch of this tree represents the best alternative without information from the base case analysis shown in Figure 3. Note that in the perfect information analysis, we simply include the decision alternative to acquire perfect information, as shown in the bottom

part of the decision tree. We know that the information source either predicts $B1$, $B2$, or $D3$ ore grade and once we have that prediction, the mine manager makes a decision as to which crusher to send the ore. Because we assume the information source is perfect, once we receive the information, there is no uncertainty regarding the ore grade. Given the perfect information, the mine manager seeks to minimize costs, so always chooses the crusher alternative with the lowest value. The value of perfect information in our case is the difference between the expected value of the perfect information alternative (\$0) and the best alternative for the base case analysis (\$1,137). Assuming perfect information, this difference represents an upper bound on the expected value of information. Of course, if there were a perfect information source available, this finding implies that the maximum amount the decision maker would be willing to pay for that source is \$1,137 per trainload.

LIF scanners, however, are not a perfect source of information. Information regarding ore grade acquired from the LIF scanners is subject to some degree of error and is therefore a source of imperfect information. For example, though the scanner indicates the load haul dump unit bucket contains $B1$ ore, there is some probability that the reading is incorrect and the ore is actually $B2$ or $D3$ grade. We are unable to obtain actual scanner accuracies, but we have chosen some representative scanner data (Broicher, 2006; Johansson, 2006) to estimate the relevant probability information (likelihood data) for our value of information approach. Utilizing these data and applying a Bayesian analysis, we are able to compute: (1) unconditional probabilities of receiving predictions of $B1$, $B2$, or $D3$ ore; and (2) posterior probabilities indicating the accuracy of the scanner predictions.

Table 4 shows a computation of the Bayesian analysis. The prior probability data are derived from the empirical results summarized in the previous section. In a Bayesian context, the events of interest, E_i , $i = 1, 2, 3$, are the existence of $B1$, $B2$, and $D3$ ore grade, respectively, and the computed prior probabilities are shown in column 2 of Table 4. The likelihood data shown in column 3 of Table 4 represent a measure of the accuracy of the LIF scanner information. For example, for cases in which the ore grade is $B1$, the scanner says it is $B1$ (“ $B1$ ”) 90% of the time, whereas for cases in which the ore grade is $B2$, the scanner says it is $B1$ 30% of the time. Given we have the prior probability estimates and the likelihood data associated with the scanner, we can then apply Bayes Theorem to compute the joint probabilities (column 4), posterior probabilities (column 5), and the unconditional probabilities (below every three rows of column 4) that the scanner predicts $B1$, $B2$, and $D3$ ore grades. We summarize these computations in Table 4 and use them in the value of imperfect information analysis in Figure 5. The accuracy of the scanner influences the expected value of the information source - in this case, the value of the LIF scanner to the Kiruna mine.

Figure 5 provides a decision tree that represents the value of the imperfect information case associated with the ore grade scanners. For readability, we display only a partial representation of the decision tree. As shown before in the perfect information case, the top branch represents the best alternative without information from the base case in Figure 3. The lower branch labeled “Scanner” is the decision alternative to utilize LIF scanners. The scanner provides a prediction of the ore type in the current train load, that is, $B1$, $B2$ or $D3$. The probabilities shown on the scanner branch (given as percentages) are those derived from the Bayesian analysis in Table 4. Given the information regarding the ore type received from the scanner, the mine operator then makes a choice to send the ore to either the $B1$, $B2$, or $D3$ crusher.¹ As noted

¹Note that in Figure 5 we only show the decision alternatives given the scanner predicts $B1$ ore. The other two branches (that the scanner predicts $B2$ and $D3$ ore) are collapsed and the expected cost of each decision is labeled

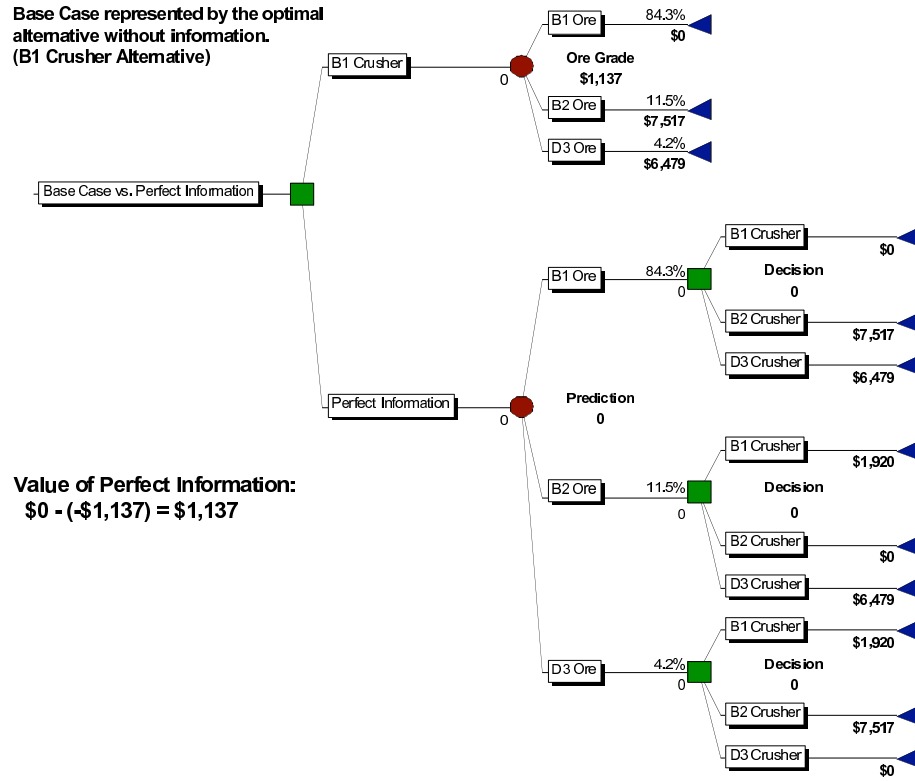


Figure 4: **Value of Perfect Information:** This decision tree analysis shows the structure of the perfect information problem. It assumes the *B1* crusher alternative is the optimal decision from the base case analysis and compares that alternative to the case in which the decision maker has perfect information about ore grade uncertainty. The top portion of the tree corresponds to the *B1* crusher alternative while the bottom portion corresponds to the value of perfect information.

earlier, there is uncertainty associated with the scanner prediction and that uncertainty is indicated by the chance nodes at the end of the branches emanating from the scanner alternative in Figure 5. The conditional probabilities shown on these chance nodes represent the posterior probabilities computed as a result of the Bayesian analysis and shown in column 5 of Table 4. These posterior probabilities indicate the likelihood of the ore type in the crusher matching the scanner prediction. For example, the probability that the ore quality is *B1* given that the scanner predicts it to be *B1* is about 95%.

Generally, the expected value of imperfect information is equal to the expected value of the information alternative, e.g., the scanner, less the expected value of the best alternative without information, e.g., the *B1*

Table 4: **Bayesian Analysis.** Utilizing Bayes Theorem, we use the prior probabilities (column 2) and likelihood data (column 3) to compute joint, posterior and unconditional probabilities for use in the decision tree analysis.

Bayesian Analysis Scanner Probabilities				
Empirical Observation:			Scanner says B1 ("B1")	
(1) Event (Ei)	(2) Prior P(B1)	(3) Likelihood P("Ei") Ei	(4) Joint P("Ei",Ei)	(5) Posterior P(Ei "B1")
B1	0.843	0.900	0.759	0.951
B2	0.115	0.300	0.035	0.043
D3	0.042	0.100	0.004	0.005
P("B1")=			0.797	
Empirical Observation:			Scanner Says B2 ("B2")	
(1) Event (Ei)	(2) Prior P(Ei)	(3) Likelihood P("Ei") Ei	(4) Joint P("Ei",Ei)	(5) Posterior P(Ei "B2")
B1	0.843	0.050	0.042	0.325
B2	0.115	0.650	0.075	0.577
D3	0.042	0.300	0.013	0.097
P("B2")=			0.130	
Empirical Observation:			Scanner Says D3 ("D3")	
(1) Event (Ei)	(2) Prior P(Ei)	(3) Likelihood P("Ei") Ei	(4) Joint P("Ei",Ei)	(5) Posterior P(Ei "D3")
B1	0.843	0.050	0.042	0.577
B2	0.115	0.050	0.006	0.079
D3	0.042	0.600	0.025	0.345
P("D3")=			0.073	

crusher. Because we are minimizing cost, the expected value of the imperfect information is the difference between the expected cost of the best alternative without information from the base case analysis (\$1,137) and the expected cost of the alternative of adopting the scanner (\$573). In the case shown in Figure 5, the expected value of imperfect information is \$564 per train load. If mine managers can obtain the scanner for less than \$564 per train load, the decision to purchase the scanner has an economic benefit to the firm.

In order to determine if the scanners are worth purchasing, we compare the cost of purchasing the scanners to the expected value of the imperfect information that the scanners provide. Given the cost of purchasing a scanner is approximately \$390,000, we estimate the initial purchase of the scanners (one for each production area) to cost an equivalent of \$85 per train load. We now compare the cost of purchasing the scanners to the expected benefit of using the scanner, i.e., the expected value of imperfect information. The difference between the expected value of information and the cost of the information is \$479 (\$564 - \$85)

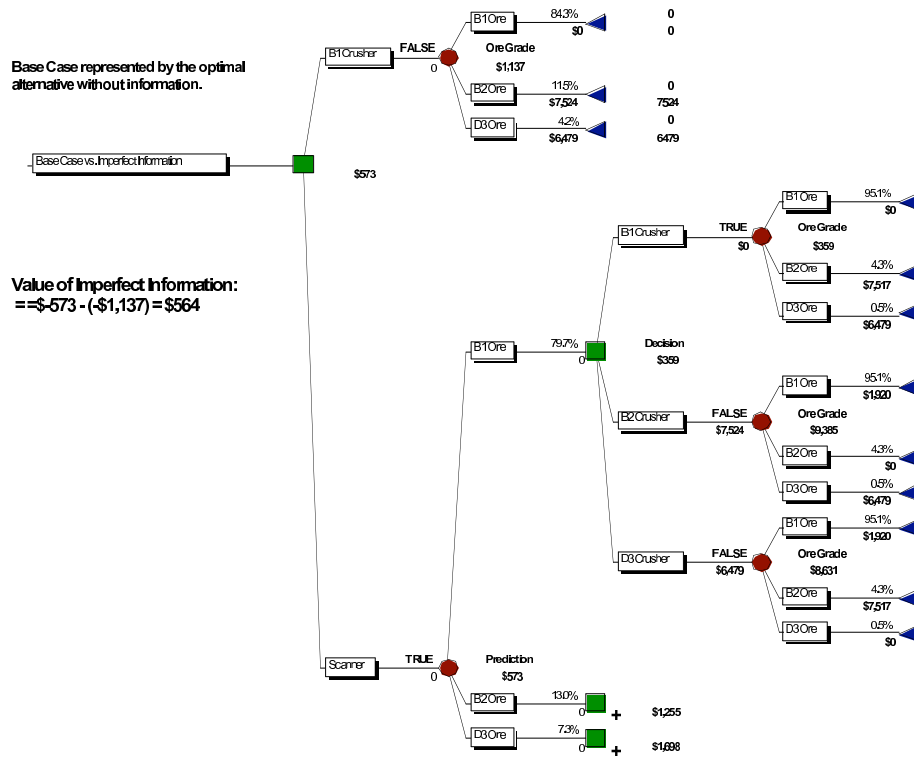


Figure 5: **Value of Imperfect Information.** This decision tree analysis shows the structure of the imperfect information problem. Again, it assumes the *B1* crusher alternative is the optimal decision from the base case analysis and compares that alternative to the case in which the decision maker has imperfect information about ore grade uncertainty.

per train load based on a typical annual number of trainloads. Although actual scanner life is greater than one year, we utilize a one-year time horizon for simplicity – *inter alia*, we can omit the maintenance cost. However, since amortization of the capital costs associated with the scanner purchase would be extended over a period greater than one year, the benefit of installing the scanners may increase significantly. The maintenance costs, time value of money, and other engineering economic effects are insignificant compared to the magnitude of the benefit observed from the value of information analysis.

The accuracy of the scanner is a critical element in the context of the mine manager's decision to purchase the scanner. We utilize sensitivity analysis to determine how robust our VOI outcome is to scanner accuracy. We focus on the accuracy of the scanner's prediction of *B1* ore because it is the most susceptible to misclassification errors. The notion here is to provide mine managers a range of scanner accuracies over which it is beneficial to purchase the LIF scanner. The scanner is only useful if the difference between the expected value of the information and the cost to purchase the information is greater than \$0. Once the expected value of imperfect information becomes equal to the information cost on a per train load basis

(\$85), then the LIF scanner offers no benefit beyond the best decision alternative without information. In order to undertake this type of sensitivity analysis, we need to revise our probabilistic calculations resulting from the Bayesian analysis. Recall that our original likelihood estimate from Table 4 was that in cases where $B1$ ore is present, there is a 90% likelihood that the scanner predicts $B1$, or in probabilistic terms, $P("B1"|B1) = 0.90$. As we perform sensitivity analysis on this likelihood data, the Bayesian analysis is updated on the revised probabilities (unconditionals and posteriors) and these new data are utilized in the decision tree analysis.

Figure 6 shows the results of a sensitivity analysis on the likelihood data versus the value of information. Our analysis shows that if the likelihood value, $P("B1"|B1)$, associated with the scanner results is greater than about 61%, then the expected value of the imperfect information is greater than the cost to purchase the information. For any scanner accuracy above 61%, the value-maximizing decision is to purchase the scanner. Clearly, there are significant increases in the value of the scanner as the scanner accuracy level improves. Our VOI approach enables us to quantify the information value differences for alternative accuracy levels. For example, the difference between the value of the scanner information and the cost to purchase the information from our base likelihood data is \$479/trainload. If we revise the accuracy of the scanner to 95%, the difference between the value of information and the cost of information increases to \$560/trainload. Decreasing the accuracy to 85% yields a value less cost difference of \$398/trainload. Given our structured approach to this decision problem, this type of sensitivity analysis could be conducted on any number of parameters in the decision model, including profits foregone and prior probability estimates.

Of course, there is a large number of trainloads each day; the empirical data suggest that there are approximately 46,000 trainloads per year. If we extrapolate our findings regarding the value of information to a one year period, we can compare the total information value to the total cost to acquire the information simply by adjusting these values by the estimated number of annual trainloads. We find that at the base likelihood probability of 90%, the total expected value of information is equal to approximately \$26 million while the cost to purchase the information is equal to approximately \$4 million. The economic benefit that arises as a result of the significant difference in the value of information versus its cost should motivate mine managers to consider the purchase and installation of LIF scanners. As mentioned above, our value of information analysis concerns solely $B1$ ore, as this ore type is the most susceptible to misclassification in LKAB's mining operations. However, similar analysis could be undertaken for the $B2$ and $D3$ ore types. For the cases in which the information value may be greater than zero, this would add to the overall benefit associated with the scanner purchases.

Results and Managerial Implications

This case study utilizes an economic decision analysis approach, vis-à-vis value of information, to provide decision makers guidance with regard to a complex operating decision in the mining sector. We first develop a methodology for identifying different types of ore misclassifications in the Kiruna mine and utilize a comprehensive cost model to quantify the impact of those misclassifications. In addition, we are able to analyze the mine data in a way that allows us to estimate an *a priori* probability of ore grade misclassification. We couple this ore misclassification and cost analysis with a decision analysis framework known as value of information. The value of information methodology assists decision makers regarding difficult choices about

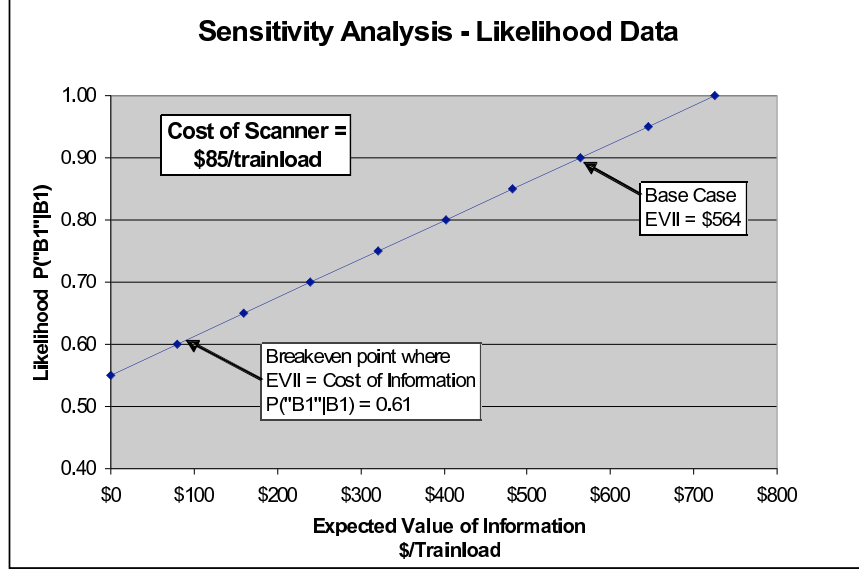


Figure 6: **Sensitivity Analysis.** This one-way (or single variable) sensitivity analysis shows the impact of changes on the likelihood data, $P("B1"|B1)$, versus the expected value of imperfect information.

purchasing additional sources of information. It enables us to explore whether the likely improvement in decision making is worth the cost of obtaining the information. In the mining context, we analyze the choice to purchase LIF scanners as a mechanism to improve the quality of operating decisions and thereby increase profitability.

Our work is based on several assumptions, e.g., cost estimates, many of them mentioned in previous sections. One other important assumption we make is the use of empirical data over a fixed horizon length to derive the prior probabilities of extracting $B1$, $B2$, and $D3$ ore, assuming mine operators are extracting ore from a $B1$ section of the orebody. This derivation is time independent in that we do not compute the probabilities over specific time intervals throughout the horizon. However, it is possible that the prior probabilities may change over time because the ore dilution associated with the mining process affects these probabilities. That is, when the mine operators begin to extract a section of the orebody designated as $B1$, initially, the probability of extracting $B1$ may be significantly higher than the prior probability we calculate (84%). However, as the mining process continues and dilution begins to occur, the prior probability of

extracting $B1$ may decrease while the probabilities of extracting $B2$ and $D3$ may increase. The change in these priors impacts the expected value of imperfect information that guides our information purchase decisions. As future research, it might be interesting to determine the optimal time (potentially subsequent to the extraction process) at which to purchase and install the scanners based on the changing prior probabilities.

The setting of our study is a sublevel caving mine. However, there are other mining and manufacturing processes that could benefit from the insights that our work provides. For example, in open pit and underground polymetallic mines, operators may be interested in extracting some combination of gold, silver, zinc, copper, lead and bauxites from the same mine. A good understanding of the mineral content of a production block (for open pit mines) or a stope or drawpoint (for a sublevel stoping or a block caving mine, respectively) would help direct the extracted material to the correct stockpile and/or processing plant for the case in which metals are separated before processing. In other industries such as semiconductor and pharmaceutical manufacturing, operators are interested to know at which stage of a complex, multi-stage process a given batch might have been misprocessed. The sooner a bad batch can be identified, the fewer additional, yet irrelevant, costly production stages are applied to the batch. Determining and applying an appropriate technique for identifying faulty batches at various stages could be worthwhile.

Although subject to some assumptions, we are confident that our results provide a strong indication that Kiruna’s utilization of LIF scanners (under certain accuracy conditions) can provide information about extracted ore grade quality that influences operating decisions in a way that leads to significant cost savings in mine operations. This improvement in information quality can also enhance Kiruna’s ability to meet production targets. Moreover, our model provides a decision tool that enables Kiruna’s managers to explore the impact of changes in scanner accuracy and the underlying cost structure of mine operations on choices managers make regarding purchasing additional information. The overall impact of this methodology can lead to significant improvement in the quality of decision making with regard to ongoing mine operations. It also provides a transparent approach to support courses of action that mine managers take regarding operations and capital investment in new technology.

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