Role of Metal Accounting in Assessing and Managing the Business Risks Involved in Production Planning

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Quantitative information about the quality of metal balance results is often overlooked when making important plant production planning decisions. Not only is this common omission made in a context where many measurements taken in and around mineral processing plants carry significant errors, but it also conflicts with the AMIRA P754 Code of Practice for Metal Accounting. The fact that metal balances are typically published without any indication of data quality may give the wrong impression that the measurements are unquestionably accurate. While it is true that statistical data reconciliation can improve the confidence intervals of redundant variables, there is no data processing technique that brings them down to zero at a finite cost. In this paper, we review the entire data flow, starting from field instruments to metal accounting-based decision-making to show how measurement errors are transmuted into business risks associated with production planning. Necessary conditions for first exposing then quantifying such business risks are stated. Pitfalls to be avoided are also discussed. Finally, a simplified risk assessment and management procedure which considers the quality of metal balance results are applied to a polymetallic mineral processing plant.

INTRODUCTION

Each and every mineral processing plant has production reporting obligations. In this paper, we are concerned with metal accounting reports (Morrison, 2008) where saleable metal flows and inventories are estimated and published. These metal accounting reports are delivered to a variety of stakeholders who use them for internal management purposes (day-to-day plant production planning, plant operation optimisation, capital spending, etc.) as well as for external management (royalty settlements, tolling agreements, etc.). Hence, there should be no doubt that spotless metal accounting is instrumental to high-quality corporate governance (Gaylard et al., 2014) of mining and metallurgical companies. To this extent, one would have expected industry-endorsed standards to have emerged a long time ago. However, the lack of an accepted set of standard procedures for metallurgical accounting was explicitly recognized as an industry-wide problem only in August 2001 during an SAIMM workshop held in Cape Town, South Africa. Discussions that followed this workshop led to the initiation of the AMIRA Project P754, "Metal Accounting and Reconciliation", in 2003.

One of the major deliverables of the Project was the development of a Code of Practice for Metal Accounting (AMIRA, 2007) for the mining and metallurgical industry. The primary objective of the Code was to provide a set of standard generic procedures and guidelines for all aspects of metal accounting, from measurement and sampling to data handling and reconciliation and reporting of results. The second objective of the Code was to facilitate risk management by enabling plant management to quantify, manage and minimize the level of risk to which it could be exposed through failures and shortcomings in its metal accounting system.

Those two objectives, logically hierarchized as business risks, cannot be evaluated in a representative fashion before a representative assessment of the raw measurements quality is made. This goes hand in hand with the fact that business risk management involves, at least partially, measurement quality management. However, this is easier said than done in the current practice because managing measurement quality has implications reaching as deep as plant design, plant construction, instrumentation retrofit and maintenance which are more than often considered as worlds apart. As a consequence, numerous authors (François-Bongarcon & Gy, 2002; Holmes, 2010; Spangenberg, 2012; Wortley, 2009) keep reporting the pervasiveness of poor measurement practices in and around mineral processing plants. Thus, it should be no surprise that few have ever reported either the fulfilment (in full or partially) of the second objective.

The sensitivity analysis of metal balances can bridge the gap between these two objectives. When attention is paid to sensitivity analysis results, the link between measurement errors and business risks can be quantitatively established and better decisions can be made. It is therefore worthwhile to revisit the metal accounting exercise with an emphasis on the assessment and management of the reported data quality.

Revisiting the Metal Accounting Exercise

The ever-expanding demand for reporting and information from mineral processing operations can create confusion, on a day-to-day basis, between metal accounting and metal reporting. Metal accounting concerns the rigorous consolidation of metal balance information while metal reporting concerns the presentation of metal balance information in formats tailored to the needs of various reporting uses and users. Such confusion has somewhat contributed to the prevalent, yet misguided, perception that a metal accounting system (MAS) is merely a reporting service. In this paper, we revisit the metal accounting exercise, keeping in mind that although, for several reasons, there are administrative silos between instrumentation, maintenance, process engineering and financial accounting departments—discontinuities are neither that clear nor advantageous within the realm of metal accounting because they preclude achieving a comprehensive quality assessment and management.

Commonplace Criteria for the Quality Assessment and Management of What is Being Reported

Like every business process, metal accounting and reporting should be continuously monitored for excellence. In the present case of metal accounting, quality monitoring is often spontaneously achieved through the reports themselves rather than through the MAS. As such, the timely availability and the self-coherency of metal reports are often the sole quality criteria routinely used for evaluating a given MAS. The latter often has an overweighed importance in the approval decision. This practice is consistent with the aforementioned misguided perception that an MAS is merely a reporting service. It will be emphasized throughout this paper that neither the avoidance of negative estimates nor the achievement of balanced numbers constitutes a satisfactory quality warranty by itself. Therefore, more meaningful quality criteria than those commonly used are needed. Those quality criteria must be connected with the end uses of metal reports, such as business risk assessment and management.

Paper Structure

We start with a brief review of the different measurement errors, thereby emphasizing their hardware origins. We then review the iterative extended data reconciliation procedure where it is shown through the sensitivity analysis that those errors, either reported or not, find their way to the metal accounting reports that are used to support plant production planning decisions. This leads the way to the inspection of the critical role of the sensitivity analysis as well as the reduced residuals analysis in obtaining a representative assessment of the measurement reproducibility. Finally, a simplified risk assessment and management procedure, which considers quantitative information about the quality of metal balance results, is applied to a polymetallic mineral processing plant.

FROM RAW MEASUREMENTS TO APPROVED PRODUCTION REPORTS

State-of-the-art reporting services have astonishing capacities for quickly producing production reports specifically tailored to a diversity of uses and users. The neatness of these reports always contrasts with the harsh production environment found in typical mineral processing sites. While reports are usually printed and consulted in offices, raw measurements are taken where mechanical vibrations, humidity, corrosion and dust, to name a few, disturb measurement devices. The report readers who are unfamiliar with the industrial environment from where the data are generated can hardly appreciate the fact that these disturbances cause measurement errors which increase the risk of business decisions made from it. As a consequence, as stated by Gaylard et al. (2014), the metal accounting function is often seen as ancillary to satisfactory operation and is, as a result, handled by junior, inexperienced technical staff or by clerical staff with no technical background. This section illustrates why this thinking needs to change.

Measurement Errors

In the current context, hardware means any mass measurement, sampling and sample analysis equipment or procedure. Each hardware measurement suffers, either sporadically or permanently, from each of the three types of measurement errors described in Table I. The main objective of this subsection is to materialize the notion of measurement errors.

Table I. Three types of measurement errors.

Type	Description	Possible remedies
Gross	Hardly reproducible Often human based Infrequent	Manual entries should be removed as much as possible Can be reduced through automation Extreme values can be detected by using validation bounds
Systematic (Bias)	Reproducible Instrument/process based Persistent	Can be minimized through good housekeeping Elimination from the outset through instrument retrofit
Random	Non reproducible Often environment based Permanent	Cannot be eliminated Can only be minimized mainly through system design (increased insulation or compensation of disturbances) Can be reduced through the use of data reconciliation

Physical (Hardware) Origins of Measurement Errors

As it will be explained later, statistical data reconciliation software alone does not remediate the problem of measurement errors, despite the fact that it is highly valuable in pinpointing measurement issues (Lachance et al., 2014). However, blindly relying on a reconciliation software package to conceal unfit for purpose measurements should be avoided right from the outset. Stating the hardware origins of most measurement errors implies that this is where they should be remedied. For example, if a sample cutter is partially blocked by dirt, thereby inducing a measurement bias, this error cannot be corrected in the software domain. As sampling biases are by nature not constant in time due to the changing nature of the material sampled and of the mass flow rate in the system (Pitard, 1993), the only recommendable solution is to actually clean the cutter. Furthermore, as convenient water supply for cleaning may be lacking, implementing a sustainable bias remediation may also involve plant retrofitting.

Likewise, the fundamental sampling error (Gy, 2004) (the random type in Table I) is caused by the very fundamental fact that ore is heterogeneous (constitutional heterogeneity in this case) and that only a limited number of fragments are selected from the lot. Solutions aiming at decreasing this random error can only involve the correct selection of an increased fraction of the lot which can only be done through plant design and retrofitting.

Quantifying Random Errors (Reproducibility)

For simplification purposes only, it is assumed that all gross and systematic errors (Table I) have been eliminated through appropriate design and remediation. Indeed, by acknowledging that such errors are pervasive in practice, this paper is quite conservative in its quantification of the remaining business risks as its scope is reduced to the sole leverage of random errors.

Random errors influence the reproducibility of achieved numbers. Thus, if another realization of the measurement process had been done, one would have obtained and reported different results while the underlying true values remained the same. It is assumed herein that all random measurement errors follow a Gaussian distribution (Figure 1) fully characterized by two parameters, namely its mean and its standard deviation. Since the mean (μ) of a random error is zero, its standard deviation (σ) is the characteristic parameter for quantifying measurement reproducibility.

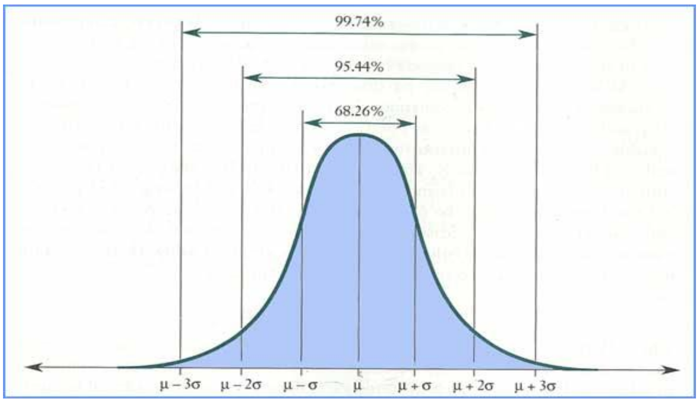

Figure 1. Illustration of a Gaussian distribution with some of its usual confidence intervals.

Each and every production data figuring inside a metal accounting report has either been directly measured or estimated indirectly through computations involving directly measured variables. However, even in the case of so-called directly measured variables such as the feed mass flow rate measured with a conveyor belt weighmeter, a scrutinising review of the measurement process would show that such direct measurements are not that direct. Such indirectness opens the door to aforementioned disturbances that generate measurement errors. Thus, each and every reported variable is, in fact, a distribution as shown in Figure 1, where only the most probable value (μ) is reported for convenience.

Illustrative Example on a Polymetallic Base Metals Mineral Processing Plant

Concepts are illustrated using published data from the now closed Brunswick No. 12 concentrator (Shannon et al., 1993) which was processing (at the time of the referred publication) near 11 000 tonnes per day of a complex lead, zinc, copper and silver ore, producing four concentrates by differential flotation. Table II shows a typical daily production balance for this concentrator.

Table II. Typical daily production balance at Brunswick Mining.

Stream	Dry weight (t)	Pb (%)	Zn (%)	Cu (%)	Ag (g/t)
Mill feed	11 000	3.2	8.5	0.37	105
Cu conc	121	6.5	3.5	22.00	2642
Pb conc	352	46.4	6.4	0.54	672
Zn conc	1419	1.8	51.3	0.29	108
Bulk conc	154	21.4	36.9	0.80	463
Tailings	8954	1.4	1.4	0.07	42

Hardware Reproducibility for the Polymetallic Base Metals Mineral Processing Plant

Hardware reproducibility (measurement random errors) for the balanced data set in Table II is not published as this was beyond the scope of the paper. For the sake of illustration, relative standard deviations observed in practice were taken and associated to the numbers of Table II to produce the simulated and unbalanced measured values of Table III. However, each mine site should continuously assess its own hardware reproducibility because this is function of site- and time-dependant factors, such as ore characteristics, equipment sizing, housekeeping, etc.

It is also assumed that each and every metal balance variable listed in Table III is actually measured, which might not be the actual case, especially for mass flow rates. Any reasonable discrepancy from those hypotheses would only affect the resulting quantitative results. The risk assessment and management procedure exposed in this paper would remain valid, regardless.

Table III. Simulated measured values with the associated hardware reproducibility (relative std).

Stream	Weight (t)		Pb (%)		Zn (%)		Cu (%)		Ag (g/t)	
	Value	Rel std (%)	Value	Rel std (%)	Value	Rel std (%)	Value	Rel std (%)	Value	Rel std (%)
Mill feed	11 754	5.0	3.0	8.0	7.9	8.0	0.35	8.0	114	16.0
Cu conc	115	3.0	6.5	5.0	3.5	5.0	22.25	3.0	2816	6.0
Pb conc	351	3.0	46.2	3.0	6.0	5.0	0.53	5.0	776	10.0
Zn conc	1409	3.0	1.9	5.0	49.6	3.0	0.31	5.0	109	10.0
Bulk conc	155	3.0	22.6	5.0	36.9	5.0	0.76	5.0	394	10.0
Tailings	9066	4.0	1.5	7.0	1.6	7.0	0.07	7.0	38	14.0

Iterative Extended Data Reconciliation Procedure

An examination of Table III confirms that simulated measured values are unbalanced. Such node imbalances can only be observed under the condition that a given metal balance model provides adequate model-based redundancy (Lachance & Flament, 2011). Data reconciliation (Bagajewicz, 2010) is a generic procedure for obtaining optimal estimates of metal balance variables under the satisfaction of usually hard constraints such as metal balance equations. It should be clear that while data reconciliation eliminates node imbalances, it does not, in any way, eliminate irreproducibility.

Table IV shows the final results of the data reconciliation procedure (to be further discussed below) where achieved numbers have been rounded off for convenience.

Table IV. Reconciled values with the associated software reproducibility (relative std).

Stream	Weight (t)		Pb (%)		Zn (%)		Cu (%)		Ag (g/t)	
	Value	Rel std (%)	Value	Rel std (%)	Value	Rel std (%)	Value	Rel std (%)	Value	Rel std (%)
Mill feed	11 354	2.5	3.2	3.2	8.2	3.4	0.35	3.3	103	5.3
Cu conc	115	2.9	6.5	5.0	3.5	5.0	22.24	2.9	2825	6.0
Pb conc	350	3.0	46.0	3.0	6.0	5.0	0.53	5.0	782	9.8
Zn conc	1408	2.9	1.9	5.0	49.4	2.9	0.31	5.0	109	9.9
Bulk conc	155	3.0	22.5	5.0	36.9	5.0	0.76	5.0	395	10.0
Tailings	9327	3.0	1.5	6.8	1.6	7.0	0.07	6.9	39	13.4

Once a preliminary production report (such as Table IV although the software reproducibility is seldom reported) is issued, the criteria upon which it has to be evaluated need to be determined. It has been said previously that neither the avoidance of negative estimates nor the achievement of balanced numbers constitutes a satisfactory quality warranty by themselves. Of course, neither of the two criteria ensures that decisions made from the report are free of acceptable business risks. The definition of better criteria requires a good understanding of the statistical data reconciliation procedure. This procedure is herein qualified as *extended* to emphasise it should include an iterative condition, as shown in Figure 2.

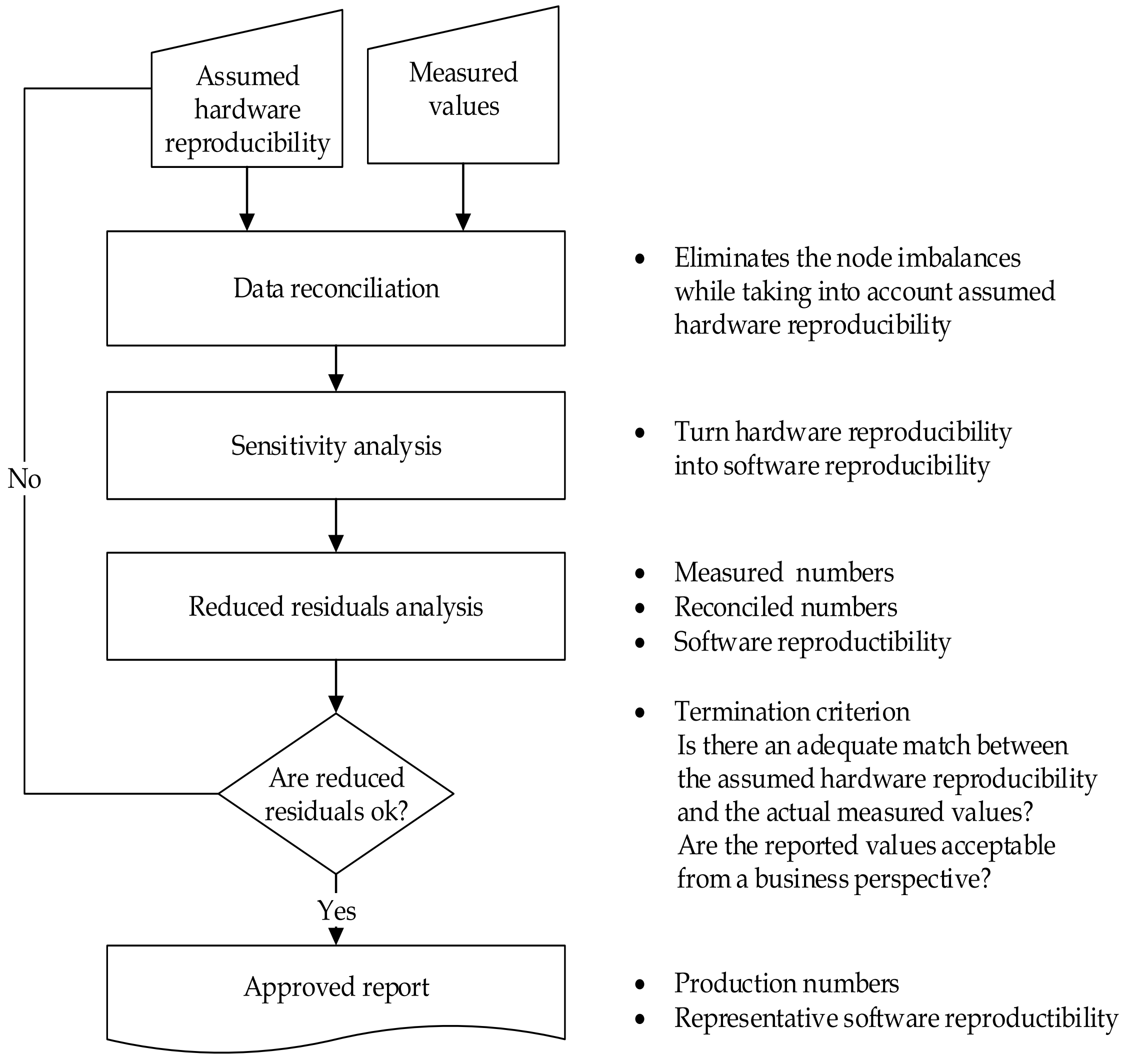

Figure 2. Simplified illustration of the iterative nature of the extended data reconciliation procedure.

Hardware Reproducibility

Most reconciliation algorithms are of the constrained nonlinear, weighted least-squares type. For a given plant configuration and a given set of chemical elements, the inputs are the measured values and their assumed hardware reproducibility, as shown in Figure 2. While measured values are usually readily available, obtaining representative numbers for hardware reproducibility is often more challenging. This is an issue in many metal accounting cases because the purpose of obtaining such representative numbers is misunderstood. It is thus wrongly believed that any number will do as long as the aforementioned misguiding quality criteria are satisfied.

Input hardware reproducibility numbers (see Table II) are represented by variances that are used as weighing factors inside the data reconciliation procedure. As such, variables that are assumed to be highly reproducible, thus associated with a proportionally small variance, will carry a heavier weight and, as such, are less likely to be adjusted. However, if that variable, assumed to be highly reproducible, is actually poorly reproducible, another variable will be wrongly adjusted for meeting the hard constraints of mass/metal conservation. Such non-representative assessment of hardware reproducibility produces a non-representative software reproducibility which, in turn, leads to non-representative risk assessment. It is thus claimed here that assumed hardware reproducibility must be tuned/identified until a representative assessment of the actual hardware reproducibility is obtained.

Data Reconciliation

Due the presence of nonlinear constraints in the metal conservation equations, the data reconciliation process (see associated box in Figure 2) is iterative. However, the algorithm is often packaged in a way that it is merely felt as an input–output process. It must be understood that, by construction, any set of input measured values fed to the algorithm will turn into a balanced output data set. Therefore, reaching a reconciled output data set is never an issue. The blind focus on this sole criterion can lead to at least one of the two following pitfalls. On one hand, stakeholders might be tempted to presolve the reconciliation issues at the outset either by eliminating any redundancy at the plant/instrumentation level (Gaylard et al., 2006) or by neglecting redundancy at the metal accounting stage, thereby applying n-product formulas (Wills & Manser, 1985). On the other hand, when redundancy is maintained and the *any means necessary* approach is taken, numbers end up being adjusted by hand, arbitrarily.

Roles of Sensitivity Analysis

The sensitivity analysis has two important roles in the extended data reconciliation procedure shown in Figure 2. Its first and most tangible role is to provide software reproducibility numbers for reconciled production numbers (see Table IV) in response to the hardware reproducibility associated with measured values. Thus, even though such software reproducibility is seldom reported in practice, sensitivity analysis is there to confirm that measurement irreproducibility does not vanish in the depth of databases. Its second role is to feed software reproducibility numbers to the reduced residuals analysis.

Sensitivity analysis is practically performed using two main methods: local (linearization) and Monte Carlo analysis. In both cases, they are input–output processes where obtaining any software reproducibility is not an issue; the actual issue is to obtain a representative software reproducibility. To this extent, one necessary condition is the presence of data redundancy (Lachance and Flament, 2011) as stated in Table V. Not only does data redundancy have this enabling capability, but it also allows the reproducibility to be improved (variance is reduced) for redundant variables.

Table V. Comparative analysis of redundant and non-redundant variables.

Variable type	Reduced residuals	Reproducibility assessment	Software reproducibility
Redundant	Defined	Enabled	Better than assumed hardware
Non-redundant	Undefined	Disabled	Same as assumed hardware

Role of Reduced Residuals Analysis

In the current context, the main role of the reduced residuals analysis (Lachance et al., 2014) is to ensure that the assumed hardware reproducibility (Figure 2) is representative of the actual hardware reproducibility. In other words, it assesses the fitness between the measured values and the assumed hardware reproducibility. For example, if a user has assumed a very high reproducibility for all measured values, but the observed node imbalances are very high, the discrepancy would be flagged by the reduced residuals analysis because the reconciled values would be too far from what was expected in view of the assumed hardware reproducibility.

Reaching an acceptable (details are beyond the scope of this brief paper) distribution for reduced residuals is the primary criterion for assessing the quality of a given metal accounting report. Therefore, a report should only be issued when the reduced residuals are adequately distributed. However, such criterion does not tell if the achieved software accuracy is fit for purpose, as will be explained below.

BUSINESS RISK ASSESSMENT AND MANAGEMENT

Actual business risk level must be correctly assessed before proceeding further with the risk management process. To this extent, several steps have already been made toward a representative business risk assessment. We have thus demonstrated the important role of sensitivity analysis in converting hardware reproducibility (Table III) into software reproducibility (Table IV). The necessary presence of model-based redundancy for achieving a representative assessment of such reproducibility via the reduced residuals analysis was also stated. However, there is nothing in the above procedure (Figure 2) that indicates whether the achieved software reproducibility is fit for purpose. In other words, we have not yet made the needed connection between the reproducibility level of metal balance results and the risk level of some relevant business processes. As has been previously stated, the business risks are not found in the metal accounting reports themselves, but rather in the decision processes that their content should assist. Through a simplified example of production planning, this section illustrates how reproducibility of the field measurements transmutes into business risks, as well as how those risks can be managed.

Business Risk Assessment for the Production Planning of a Zinc Mining Operation

For simplification purposes, only the business risk associated with the planning of zinc production at the now closed Brunswick mining operation is considered. According to the numbers of Table II, Brunswick had a nominal production of about 20 000 tonnes/month of zinc in concentrate. If Brunswick sold zinc concentrate in lots of 20 000 tonnes each, they would have needed to make a decision to produce another lot at the end of each month. This was well before they could expect to be paid in full by the customer of the concentrate lot. The time that elapsed from the beginning of mining until the casting of zinc ingots was significant. For the sake of this discussion, it will be assumed to be three months. Neither the future LME spot price for zinc nor the payable quantity was known precisely at the time of taking the decision. Of course, the assessment of payback always improved over time as zinc was transported along the processing chain from the orebody to the ingot storage area at the smelter. Once transformed into ingots, electrolytic zinc has a nominal zinc content of 99.995 % and its mass can then be measured very accurately with static weigh scales. Of course, such high accuracy of zinc payable quantity is not available when the decision to mine the block of ore must be taken.

Investigating the Revenue Risk

In this simplified scenario, revenue is defined as:

$$revenue = price \times mined\ dry\ tonnes \times mined\ grade \times mill\ recovery \quad [1]$$

where a simplified payment scheme is assumed where no penalties are applied, smelter recovery is 100 % and 100 % of produced zinc is payable. Table VI shows the details of each identified revenue risk factor in relation with Equation [1], where it can be seen the reproducibility of the mill recovery has been greatly improved by the data reconciliation procedure.

Table VI. Values of the parameters used to assess the revenue risk.

Risk factor	Type	Nominal value	Hardware reproducibility (%)	Software reproducibility (%)
Price	Currency	US$ 2000 /tonne	5.0	5.0
Mined dry tons	Quantity	11 000 tonnes/day	5.0	5.0
Mined grade	Quantity	8.5 %	8.0	8.0
Mill recovery	Recovery	77.7 %	10.5	1.6

As no repeatability factor was included in the mill recovery reproducibility, it is assumed that operators are able of achieving a constant zinc recovery for similar lots. Thus, the assumed reproducibility numbers in Table VI are totally caused by measurement irreproducibility.

Illustrating the Business Risk

In order to illustrate the business risk, we define a profitability index (p.i):

$$profitability\ index = revenue/cost \qquad [2]$$

For simplification purposes only, we have chosen to ignore the variability of costs which are usually better known than revenues (Morrison & Grimes, 2001) when the production planning decision is made. Nominal production costs for a lot are assumed to be US$ 36 000 000/lot using a marginal cost of US$ 1800/tonne (20 000 tonnes/lot x US$ 1800/tonne).

The notion of risk is indissociable from the notion of probability of an unfavourable outcome as well as from the magnitude of the unfavourable outcome itself. In the current case, the unfavourable outcome was set to be the absence of profitability (p.i. < 1). Using the software numbers of Table VI, Monte Carlo simulations were conducted for calculating the business risk associated with this uncertainty. Figure 3 (right) shows that the assumed uncertainty brings a cumulative risk of around 20 % that mining the targeted block of ore will not be profitable while Figure 4 shows that removing the uncertainty brings a total certainty about reaching profitability.

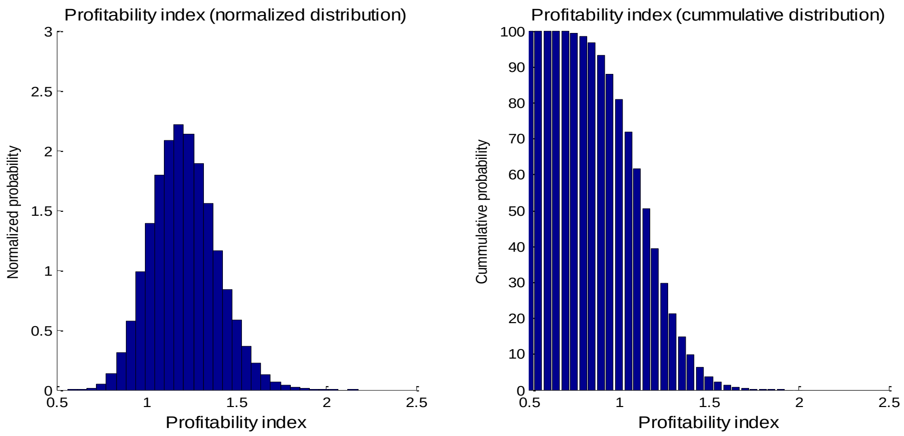

Figure 3. Normalized and cumulative distributions of profitability index using Table VI (hardware).

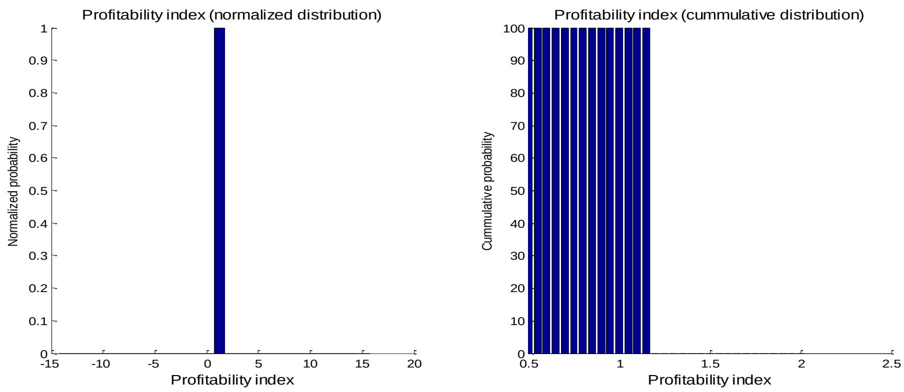

Figure 4. Limiting case where there is no uncertainty associated with parameters of Table VI.

Business Risk Management Process
In the above example of business risk assessment, the uncertainties on price and payable quantity were related to one another in an equation. Thus, as it can be seen from Figure 3, a tangible cause and effect relationship can be established between measurement reproducibility and business risks. As such, it should now follow naturally that managing the profitability risk associated with production planning basically involves managing measurement reproducibility (or quality in a more general context).

Managing Measurement Quality
Once the tolerance for business risks is determined, risk management can proceed. Considering the challenges associated with taking representative measurements and samples in mineral processing plants, it is likely that the initially computed risk will be higher than expected (Wilke et al., 2009). So, for narrative purposes, we will assume that the initially computed risk level is unacceptable.

An unacceptable business risk related with Figure 3 can be managed along two variables, namely the price and the payable quantity. Hedging is a well-known technique to handle the price volatility, especially the risk of falling prices. Although, going further in this direction goes beyond the scope of this paper, it should be kept in mind that both dimensions go hand in hand because neglecting the delivered quantity could offset the benefits of the hedging programme. In fact, it is possible that improving measurement quality may be more cost-effective than hedging for reducing business risk.

Should it be decided to improve the actual software reproducibility, either or both of the following remedies could be envisaged:

- Retrofitting the existing instrumentation (increasing hardware reproducibility);
- Adding new measurements (devices, analyses, etc.) in view of increasing redundancy;

Each remedy will involve costs associated with hardware, software and maintenance. Consequently, the selection and design of the remedy should be based upon the reduction of risk that it would provide. This measurement quality management process is a continuous process that requires maintenance. The benefits generated after the initial implementation of a remedy will therefore fade away under poor instrumentation maintenance.

CONCLUSIONS

Managing Business Risks Involves Managing Measurement Quality
The primary objective of the Code of Practice for Metal Accounting was to provide a set of standard generic procedures and guidelines for all aspects of metal accounting, from measurement and sampling to data handling and reconciliation and reporting of results. The second objective of the Code was to facilitate risk management by enabling plant management to quantify, manage, and minimize the level of risk to which it could be exposed through failures and shortcomings of a metal accounting system.

In this paper, we have illustrated the importance of good metal accounting practices for assessing and managing the business risks involved in production planning and more specifically, for obtaining a reliable assessment of the risk associated with the future payment of an uncertain metal production. The main conclusion is that significant business risks are taken when insufficient attention is paid to measurement quality. This can be thought-provoking for those who tend to relate business risks with metal price fluctuations only. When the importance of measurement quality is recognized, however, instrumentation maintenance and sampling quality control management become central to business risk assessment.

State-of-the-Art Metal Accounting System

Risk management and metal accounting meet through the design/retrofit/maintenance of state-of-the-art MAS that are fully compliant with the AMIRA P754 Code of Practice. Unfortunately though, this relationship is rarely recognized by plant management (Gaylard et al., 2009). Managing measurement quality truly has implications reaching as deep as plant design, plant construction, instrumentation retrofit and maintenance. To this extent, AMIRA P754 reported that (1) some management layers might lack technical inclination about how measurement quality management should be undertaken and (2) that some political issues might be involved by appointing a competent person to the task. In view of the issues raised previously, the competent person has a major role in bridging the gap between high-level corporate risk management objectives and measurement quality control. Hopefully, this effort will encourage practitioners to revisit their metal accounting practices.

Revisiting the Metal Accounting Exercise

Through the principles promoted by the AMIRA P754 report, what used to be perceived as a mere reporting task has moved to a structured multidisciplinary discipline where an MAS system encompasses hardware, software and people. The design, construction and implementation, and maintenance of such system require a management framework, as for any other engineered system.

We have thus reviewed critical elements of a modern metal accounting system, stressing the importance of achieving a reliable assessment of the actual hardware reproducibility. This has triggered the search for meaningful criteria for the approval of both a metal accounting report and an MAS system. It was emphasized that neither the achievement of balanced numbers nor the absence of negative values should be considered as valid quality criteria for report approval. Moreover, those invalid quality criteria are well-known for supporting *any means necessary* approaches where data are adjusted by hand through a path of least resistance. This practice often ends up being economically detrimental in the long run. It was thus stated that achieving an acceptable distribution for reduced residuals should be the primary quality criterion for report approval. The adequate distribution of reduced residuals ensures that the hardware reproducibility is assessed in a representative fashion and that, as such, reconciled numbers are optimal estimates. Since reduced residuals are only defined for redundant variables (see Table V), obtaining such data redundancy is a necessary condition for the representative assessment of business risks.

This sole condition, however, is not enough for approving the design of an MAS system. Not only should an MAS system provide a reliable assessment of the reproducibility, but it should also provide reliable estimates of metal flows. Such representativeness is achieved when the estimators are free of biases and have a reproducibility level that is fit for purpose. That fit-for-purposeness must be connected with the end uses of metal accounting reports, such as business risk assessment and management. For the scope of this paper, an MAS system should only be approved, after a thorough audit and a business analysis, if the business risks are within a range deemed acceptable by management, as it has been recommended by AMIRA P754. Such an MAS system design, once made compliant with qualitative issues, will result from a trade-off between cost and the level of business risk that management is comfortable with.

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