GEOMETALLURGY APPLIED IN COMMINUTION TO MINIMIZE DESIGN RISKS

*M. Bueno[1], B. Foggiatto[1] and G. Lane[1]

[1]*Ausenco*
144 Montague Road
South Brisbane, Australia QLD 4101
*(*Corresponding author: marcos.bueno@ausenco.com)*

GEOMETALLURGY APPLIED IN COMMINUTION TO MINIMIZE DESIGN RISKS

ABSTRACT

Every comminution testwork program should include the appropriate ore characterisation tests to describe the variability of ore breakage properties, but there are several ways to interpret the data and define the design criteria for a project. The most simplistic way is to adopt an arbitrary value, such as the 80^{th} percentile ore properties. This is typically used in pre-feasibility and feasibility studies to mitigate risks, but it does not account for the actual feed variability. Alternatively, there are geometallurgical approaches that consider the mine sequencing and the characteristics of different ore types. This paper describes a method that applies geometallurgy and multi-scenario simulation to minimize risk in comminution circuit design.

KEYWORDS

Geometallurgy, comminution circuit design, risk analysis, Monte Carlo

INTRODUCTION

"What are the chances of achieving design throughput throughout the LOM of a project?" Armed with answers to this question, one could take a lot of guesswork out of decision-making in mill design and plan strategies with more confidence. There are two main root causes of faults in mill designs: the selection of wrong design criteria and the use of poor design methodologies or inaccurate models. The selection of wrong design criteria occurs mainly due to lack of quality testwork or misinterpretation of results and orebody variability.

Orebodies are intrinsically variable in composition and physical properties by the virtue of their heterogeneous nature. There are few orebodies that consist of one single lithology or any other geological classification (ore types). This variability is usually evident from orebody characterization programs by showing the spatial distribution of these properties. Orebody complexity is well recognized, however, the design of most processing plants is still performed using fixed or discrete values of the orebody properties as input parameters. Designing a process plant has many conventions and one of these is that selecting the 80^{th} percentile value of a key measure, such as the JK drop weight test Axb parameter (Napier-Munn el.al., 2005), the SMC Test® drop weight test index (DWI) (Morrell, 2004), the SAG power index (SPI®) (Starkey & Dobby, 1996) and Bond ball mill work index (BWI) (Bond, 1961), provide unquestionable margin of design safety in the plant (David, 2013). However, this approach does not consider the inherent variability of the orebody and, therefore, can lead to results which are not representative for some of the ore types.

Monte Carlo simulation is a mathematical technique that allows accounting for risk in quantitative analysis and decision making. In this paper, risk analysis using Monte Carlo simulation is used to analyze the effects that orebody variability has on the circuit performance and the probabilities they will occur, i.e. the likelihood of achieving design throughput or not. This methodology is an alternative way of applying geometallurgy and multi-scenario simulation in the design of a circuit featuring AG/SAG mills. The method relies in using statistics to analyze geometallurgical and mining data to model the variability of specific energy requirements of SAB (SAG and ball mill) and SABC (SAG and ball mill with-pebble crushing) circuits for mill design purposes. Ultimately, an example is presented to demonstrate the application of this method can be used to evaluate and minimize design risks.

GEOMETALLURGICAL MODELLING

Geometallurgy has been increasingly utilized to understand orebody variability by integrating geology and metallurgy. In a typical geometallurgical program, ore types across the orebody are characterized in terms of ore hardness, liberation size, energy consumption and metal recovery, and metallurgical performance indices are mapped across an orebody. The knowledge of intrinsic geological properties and their relationship to metallurgical response enables the application of an integrated approach to spatially map performance indices and predict metallurgical performance (Dobby et al., 2004).

According to Kittler et al. (2011), the objectives of a geometallurgical program can vary, depending on whether it is supporting a project under development (processing circuit design) or an existing operation (throughput forecasting). Geometallurgy is a tool used to assess options for mine development and production planning in both situations, aiming at reducing risks and maximizing project value. Figure 1 shows a schematic block diagram for applying a functioning geometallurgical program.

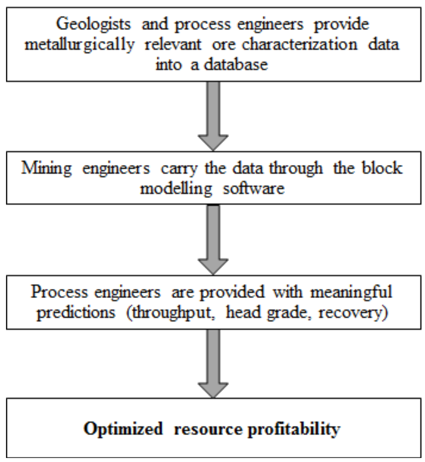


Figure 1 – Block diagram for optimizing resource profitability by geometallurgical programs. Adapted from David (2013).

As the emergence of geometallurgical studies dates mostly from 2000 and onwards (Williams, 2013), most of these methods are still under validation. A few different methods have been developed to spatially map geological and metallurgical characterization data, which include:

- Standard spatial interpolation methods such as inverse distance or geostatistical methods such as kriging (Dagbert & Bennett, 2006; Amelunxen et al., 2001; Bergholz & Schreder, 2004),
- A range of recognized statistical techniques such as Principal Component Analysis (PCA), multiple linear and non-linear regression modelling) to incorporate processing-performance domains into spatial models (Keeney & Walters, 2011; Keeney et al., 2011),
- Use of drill core logging, lithology, chemistry and mineralogy data to create a geochemistry model that provides data to define processing performance (Hunt et al., 2013), and
- Combined kriging and PCA (Deutsch, 2013).

A few examples of published successful geometallurgical programs are described in Table 1. These geometallurgical methods were used to populate a block model with comminution indices (e.g. BWI, DWI) are extremely useful for throughput forecasting and mining optimization. However, these methods can introduce other sources of error to the existing data due to poor correlations between geological and metallurgical data, kriging non-additive data (Shaw et al., 2013) or even lack of special testwork data density, which may lead to biases and consequently faulty mill designs.

Table 1 – Examples of published geometallurgical programs.

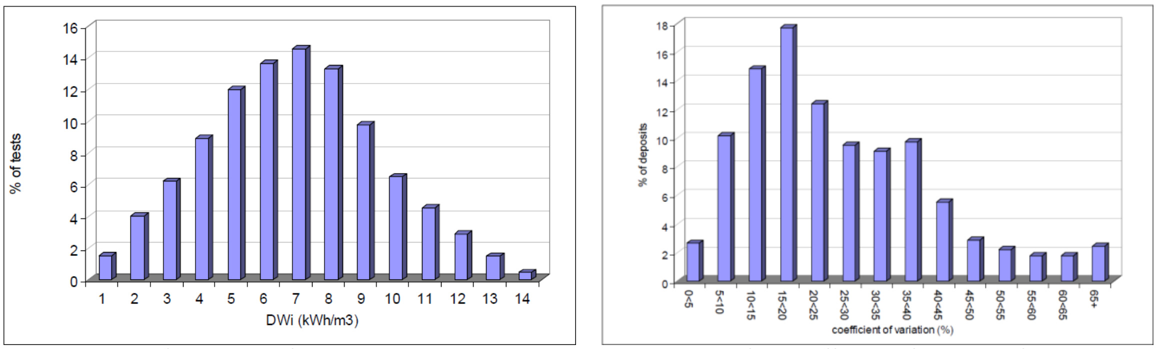
Site	Source	Description
Newcrest Cadia	Keeney et al. (2011)	An alternate integrated geometallurgical mapping and modelling method was applied to model and map comminution performance at Cadia East. The data set included assay measurements, geological logging information and comminution measurements, which were used to develop models for comminution indices (i.e. A×b, BWI, and throughput) based on inherent geological variability. Domains were identified using predicted A×b, BWI, and throughput models. In this case, the predictive models indicated that class-based comminution models were more robust than traditional universal models.
Batu Hijau	Wirfiyata & McCaffery (2011)	Geological and geotechnical characterization data, metallurgical and hardness parameters were used in the throughput estimation model. Initially, a sixteen domain throughput model based on lithology and ore hardness domains was developed. After a review of this model, an alternative approach was proposed, which combined the available milling power draw, the rock quality data (RQD) and a function relating copper grade and drop weight index (DWI), and work index independently of ore domains.
Freeport-McMoRan's project	Amelunxen et al. (2011)	The trade-off economics of SAG mill and HPGR-based circuits were primarily determined for the average ore hardness, and then the performance of the two circuits were modelled over the LOM hardness and head grade plans, resulting in estimated throughputs, grinds, and recoveries for each year. However, daily/weekly inefficiency and process constraints resulting from hardness variability trends were ignored as the LOM plan was based on annualized averages. The short term variability was analysed by Amelunxen et al. using Monte Carlo simulation techniques. Incorporating hardness variability in the trade-off study resulted in an increase of the project net present value when considering annual/daily hardness variability.
Escondida	Bergholz & Schreder (2004) and Flores (2005)	Geometallurgy was applied both in the design and plant operation of the Escondida project. These programs provided a better understanding of the hardness variability in the orebody and also were useful for optimizing the design of the comminution circuit expansion as well as for forecasting mill throughput.

Ore Type and Variability

There are different interpretations of what constitutes an ore type (also termed a domain or a class) in the context of geometallurgy (Amelunxen, 2001; Dagbert & Bennett, 2006; Keeney & Walters, 2011; Amelunxen et al., 2011; David, 2013; Williams, 2013). In the present study, it was considered that an ideal “geomet” ore type has a distinct physical property or process response in relation to the other types, and that the variability of these parameters should be relatively low for a single ore type population.

Some geological properties such as oxidation state, lithology and alteration are often used to classify ore types in geometallurgical programs. However, these properties may not necessarily have correlation with comminution behavior. In these cases, it is recommended that multivariate analyzes be conducted such as PCA with geochemical, mineralogical and preliminary or proxy metallurgical data to identify classes of geomet ore types.

Once the geomet ore types are identified based on a few preliminary tests and analysis, a robust testwork program can be planned to capture and describe the variability of ore breakage properties (e.g. A×b or DWI, BWI) and their inherent correlation in the orebody. Morrell (2011b) suggested that the minimum number of samples to conduct this preliminary analysis is around ten for an orebody with an assumed coefficient of variation between 15 to 25% (see Figure 2b). The analysis of the variability of these initial samples provide an indication of the real variability and can be used to estimate how many samples need to be treated to achieve the accuracy required for the pre-feasibility study and the following stages of the project.



a) Histogram of DWI Values from SMC Testing Data Base (17000+ data points)

b) Histogram of the Coefficients of Variation of DWI Values (based on values from 650 deposits)

Figure 2 – Distributions of DWI values and coefficient of variation within SMC test database. Reprinted from Morrell (2011b).

According to classical statistics, the sample size required to meet a desired margin of error can be calculated using the following relationship:

$N = \frac{(z^2 \times s^2)}{e^2}$, where
z = zeta probability associated with the desired level of confidence
s = standard deviation (= coefficient of variation x mean)
e = desired margin of error.

This relationship can be a guide for metallurgists to define how many samples should be tested at different stages of a project. Considering an ore type with an average DWI of 7 kWh/m^3 and coefficient of variation between 15 to 20% as an example, this relationship suggests that eight samples or more should provide a margin of error equal to or below 10% (0.7 kWh/m^3) with 90% of confidence (z = 1.645).

Some traditional approaches to plant design are based on a small number of composite samples that are believed to represent the orebody blend for a given mining period. However, compositing may hide and smooth the natural variability of the deposit which in fact should be the focus of any reliable design method. David (2013) argued that the use of composites removes a lot of the variability inherent in the data and thus will misrepresent the true variability of the feed. In this instance, if additional variability data cannot be obtained or inferred from another metric, it is prudent to select the hardest composite as the design criteria, or even the hardest plus a factor. In this way, the design criteria value would represent the competency of sample X, which is the composited average of ore type Y and represents Z% of the orebody (or similar).

One could also argue whether the variability measure by the testwork data does represent real variation for a given ore type, or are just a reflection of experimental error (i.e. the uncertainty in making the measurement)? The study by Stark et al. (2008) revealed that a good measurement of A×b has an experimental standard deviation (SD) of approximately 4% of the mean value due entirely to experimental error in the drop weight test conducted by only one operator. If an operator effect is introduced, the SD can more than double. The authors presented that when this effect was considered, a SD of 3.8% of mean throughput was obtained for 100 JKSimMet simulations of a simple SAG circuit in which only the A×b was varied by this amount. The 95% confidence interval of throughput would of course be about twice this value, so there is some real uncertainty in throughput prediction as a consequence of uncertainty in the experimental value of A×b alone (not related to the real differences in ore types – that is additional).

COMPETENCY AND HARDNESS

Competency as measured by A×b, DWI or SPI, and hardness as measured by BWI are two different properties that have distinct effects in the comminution process. Ore competency is directly related to SAG mill specific energy and hence throughput, while hardness has great influence on ball mill specific energy requirements and grind size. Therefore, it is important to understand their correlation, especially when designing SAB or SABC grinding circuits.

Design criteria based the 80th percentile of these two different properties typically leads to a competent-hard combination, as per the possible combinations shown in Table 2. However, orebodies may present hard but not competent material that is not accounted for if the 80th percentile method is used. Thus, the correlations between the different comminution properties, which may be strong, also have to be considered. This is occasionally overlooked in the design process. In any given simulation, these parameters cannot be selected independently, and one must allow for the correlation between comminution properties.

Table 2 – Ore competency and hardness classification.

DWI (kWh/m^3)	**BWI (kWh/t)**			
	<10	**10 – 15**	**15 – 20**	**>20**
> 8	Competent Soft	Competent Moderate	Competent Hard	Competent Very Hard
4 - 8	Moderate Soft	Moderate Moderate	Moderate Hard	Moderate Very Hard
< 4	Friable Soft	Friable Moderate	Friable Hard	Friable and Very Hard

The relationship between DWI and BWI plotted in Figure 1 comes from a dataset that is later used in the case study presented in this paper. The graph was divided in four quadrants, indicating the average values of the competency and hardness parameters presented in each axis. The red point represents a typical design criteria based on the 80th percentile of DWI and BWI values, which was considered to provide a conventionally accepted margin of design safety. However, ores with a lower DWI value would result in a higher SAG mill throughput and coarser transfer size, thus changing the power split between the mills. This means that a ball mill designed for competent rock would be underpowered to achieve the design grind size and subsequently compromise metal recovery. Hence, the selection of these parameters for design should consider the actual correlation between competency and hardness.

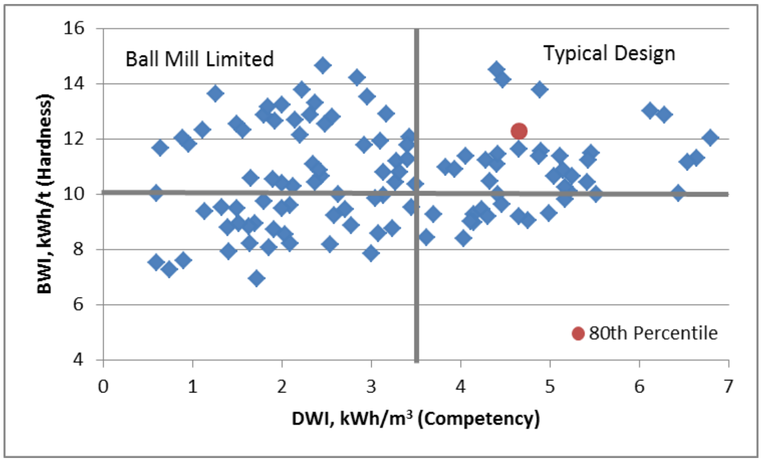


Figure 1 – Breakage characteristics dataset of one selected project.

What would be the 80th percentile represent for a bimodal dataset composed of two different ore types in a mine plan? At the extreme, it might fall between the two data sets, in which case it is the 100th percentile of ore type 1 and the 0th percentile of ore type 2. In this instance the plant may fail to perform when treating ore type 2. Therefore, information such as the proportion ore type 2 present in the mine plan and how it will be presented (i.e. is it a consistent proportion of the feed or is it 100% of feed for the first two years?) are needed. The answer to these sorts of questions is critical to selecting the design criteria.

SAB/SABC circuit design implications

Bond's method is widely used for determining the specific energy (Ecs) for crushers, rod mills and ball mills, whilst several methodologies and related standardized laboratory tests have been proposed over recent decades for AG/SAG mills. Test such as autogenous media competency test (AMCT), JKDWT, SMC, SPI or SAGDesign tests are used to measure the ore competency and calculate the Ecs for AG/SAG mills.

Some design methods (Lane et al., 2013, Morrell, 2004, Siddall & Putland, 2007) predict the total comminution energy requirements of SAG mill-based circuits using work indices measured in laboratory and Bond-style power based models, while the SAG Ecs is calculated independently using empirical models as a function of measured ore competency (Morrell, 2003, Daniel & Wang 2014). Consequently, the ball mill Ecs calculated is the residual (i.e. Total Ecs – SAG Ecs).

Another way of determining the power split between the SAG and ball mill stages is by estimating the transfer size (T_{80}) and calculating the ball mill Ecs using Bond-style calculations (Barratt & Allan, 1986; Starkey et al., 2006; 2009; Burgess, 2012). In these methods, the SAG mill Ecs is also estimated from ore competency and the total specific energy is the sum of SAG mill and ball mill Ecs values. Morrell (2011a) demonstrated that these methods rely on the assumption that the transfer size distribution is normally parallel to the cyclone overflow size distribution. Quite often, however, this is not the case. Thus, the power split can vary considerably according to the selected T_{80} value, as shown is Table 3.

Table 3 – Example of the use of power-based equations using T_{80} values. Reprinted from Morrell (2011a).

BWI (kWh/t)	F_{80} (µm)	T_{80} (µm)	F_{80} (µm)	SAG mill specific energy (kWh/t)	Ball mill specific energy (kWh/t)	Total mill specific energy (kWh/t)
15	100,000	6,200	180	3.3	9.3	12.5
15	100,000	3,000	180	4.1	8.4	12.5
15	100,000	1,600	180	5.1	7.4	12.5

Regardless of which method or model is being used, it is clear that the higher the level of conservatism in the ore competency, the lower will be the ball mill specific energy requirements. Therefore, the design criteria for ore competency (e.g. A×b, DWI, SPI) have a significant effect on the power split between SAG and ball mills in SAB/SABC circuits and can totally misrepresent the mill selection if not properly selected.

The importance in understanding and accounting for the correlation between competency and hardness in comminution circuit design are discussed further in the following section.

MILL DESIGN USING GEOMET AND RISK ANALYSIS

Instead of relying on arbitrary selection of design criteria, a new method for combining geometallurgy and a Monte Carlo simulation to understand the variability of comminution design parameters is proposed. The simulation can show many possible outcomes from the Ausgrind comminution model (Lane et al., 2013) and determine how likely these are to occur. It mathematically and objectively computes and tracks many different possible scenarios, revealing the probabilities and risks associated with each one. Thus, it is possible to decide which risks to take and which ones to avoid, allowing for the best decision making under uncertainty.

The method requires a number of testwork measurements on identified geometallurgical ore types. The required number of samples per lithology may vary, depending on their occurrence and variability. The mine schedule provides the mass proportion of each ore type (adding to 100% of mill feed) to normalize the testwork data. Then Monte Carlo simulations using the weighted testwork data can produce a relatively large number of SAG and ball mill specific energy estimates and thus mill capacities which represent the ore body for a defined production period. Once this distribution of estimates is calculated, all possible scenarios are analyzed and the design criteria are established for a certain level of contingency (e.g. percentiles or SDs). The equipment is sized accordingly and the design is validated by conducting risk analysis on mill throughput which determines the probabilities of high, low or intermediate capacities during the period of interest. Essentially, the method relies on the major steps illustrated in Figure 4 and listed as follows:

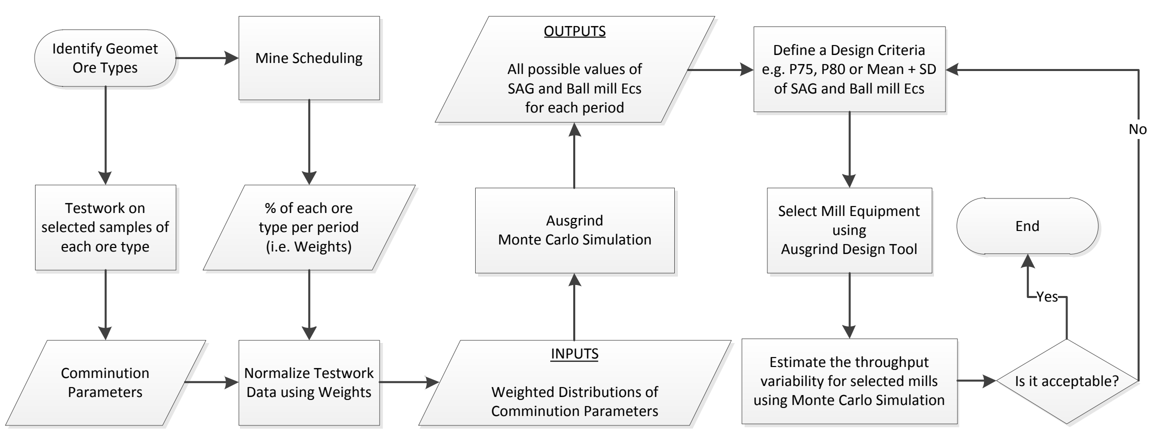


Figure 4 – Block diagram of the statistical method for selecting design criteria.

1. Identify distinct geomet ore types using PCA with geochemical and preliminary metallurgical test data. Ideally, this classification should also hold spatially. Alternatively, geological classifications such as oxidation state, lithology or alteration can be used if these are capable of describing the comminution behaviour.

2. Design and conduct a testwork program that allows for enough samples to be tested and understand the variability of metallurgical properties of each geomet ore type, also matching their overall quantities in the orebody.

3. The amount of each ore type in the mine schedule is used to obtain the weighted variability? of comminution parameters, as well as the correlations between them for a mining period which can be a day, a month or a year.

4. A Monte Carlo simulation tool coupled with Ausgrind is then used to calculate all possible values of SAG and ball mill specific energy requirements for each mining period, according to the mine schedule.

5. The risk is assessed and the design criteria are established using a certain level of contingency, which could be a percentile (e.g. 80^{th}) or the mean plus one SD. However, the criteria may be critically selected in case an unusual feed condition or other project specific requirements need to be considered.

6. The mill equipment is then sized using the Ausgrind design tool, which relies on in-house design margins and the Morrell (1996) power model to select the appropriate mill shell and motor to achieve the required power at established nominal and maximum operating conditions. A risk analysis simulation is conducted to estimate the throughput variability to assess the probability of high, low or an intermediate capacity during the period of interest and to validate the design.

7. If it is identified that the selected mills have a high risk of not achieving throughout for a period of interest, the level of contingency adopted in the design criteria can be can be increased or decreased to suit the project appetite for risk.

Kosick and Bennett (2001) developed a similar methodology using the CEET® program, which differs from this methodology in two main features. Firstly, the comminution models used in CEET are fundamentally different from those available in Ausgrind. CEET® uses SPI as the input and relies on the estimation of transfer size to determine the power split. In contrast Ausgrind uses a Bond-style power model to estimate total specific energy and an empirical model to estimate the SAG mill Ecs as a function of DWI (or other comminution parameters), as described in Lane et al. (2013) and operating conditions. Secondly, most published applications of CEET® (Amelunxen et al., 2001; Bulled, 2007; Kosick et al., 2002; McInnes et al., 2002) have used block model data in Monte Carlo simulations, while the proposed method uses the actual testwork results only, and weighted using mine schedule information for design purposes.

Case Study

This methodology was recently applied in a feasibility study for a 15 Mt/y copper project. The testwork program was conducted for ten different ore type classifications that had been established using geological interpretations such as lithology and alteration. The amount of samples selected for each ore type reflected their overall amount in the orebody, as shown in Figure 5. The summary statistics for the main comminution parameters measured in the testwork are presented in Table 4.

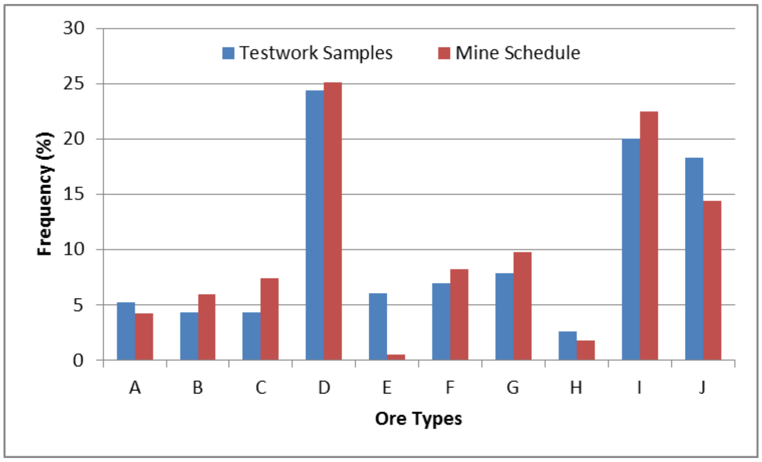


Figure 5 – Sample frequency according to ore types and their overall frequency in the orebody

Table 4 Summary statistics of comminution testwork data for the different ore types

Ore Type	**Sample Size**	**DWI**		**BWI**		**SG**	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
A	6	2.1	0.9	8.7	0.8	2.9	0.4
B	5	4.5	1.4	11.5	0.3	2.5	0.1
C	5	4.2	0.9	10.5	0.8	2.5	0.0
D	28	2.0	0.6	11.5	1.9	2.5	0.1
E	7	1.1	0.5	8.6	1.7	2.3	0.1
F	8	2.9	1.5	11.0	2.6	2.3	0.1
G	9	2.6	0.9	10.4	1.3	2.4	0.4
H	3	3.1	1.2	12.8	2.0	2.6	0.1
I	23	3.9	0.9	10.5	1.2	2.6	0.1
J	21	4.9	1.2	10.5	1.3	2.6	0.1

* 95% CI is the 95% confidence interval

The distributions of DWI, BWI and SG illustrated in Figure 6 show that most ore types have distinct physical property or process response in relation to one another, and the variability of these parameters is relatively low for a single ore type compared to the whole population. A one-way ANOVA analysis of the DWI, BWI and SG variances were also conducted, indicating that there are significant differences among the means of ore types at the 0.05 level of significance. These differences are summarized in Table 5.

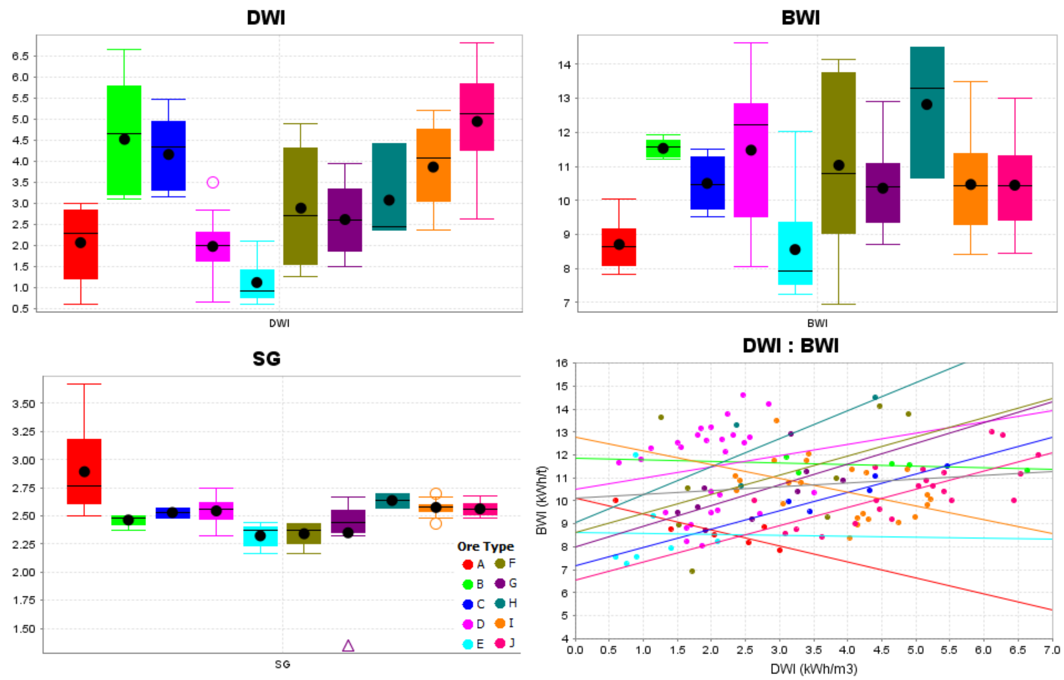


Figure 6 - Distribution of DWI, BWI and SG values

Table 5 – Significant differences detected by ANOVA

Ore	A	B	C	D	E	F	G	H	I	J
A	-	BWI		BWI					BWI DWI	BWI DWI
B	BWI	-		DWI	BWI DWI					
C			-	DWI	SG DWI	SG				
D	BWI	DWI	DWI	-	SG BWI	SG			DWI	DWI
E		BWI DWI	SG DWI	SG BWI	-		DWI	SG	SG DWI	SG DWI
F			SG	SG		-		SG	SG	SG
G							-			DWI
H					SG	SG		-		
I	BWI DWI			DWI	SG DWI	SG			-	
J	BWI DWI			DWI	SG DWI	SG	DWI			-

The mine schedule presented in Figure 7 was then used to normalize the testwork data according to the amount of each ore type for a period of interest. The testwork and weighted DWI, BWI and SG distributions are presented in Figure 8. The testwork and LOM distributions are quite similar, which is an indication that the sample selection represented the amount of each ore type in the orebody. The weighted distributions vary quite significantly throughout the LOM and it is noticeable that the variability of competency is greater than that for hardness.

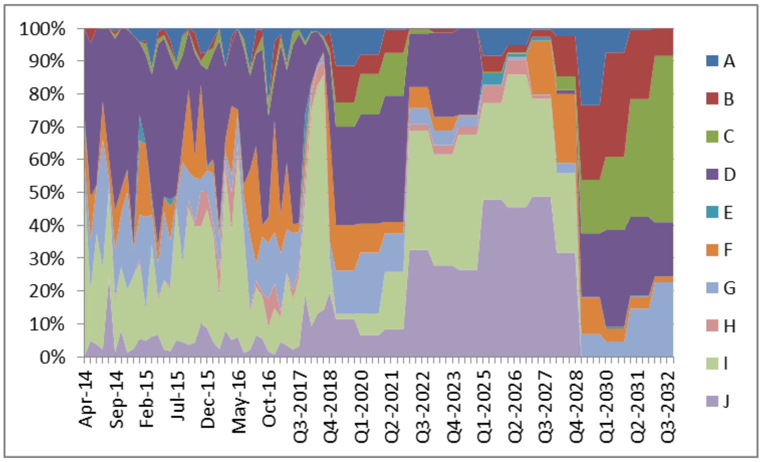
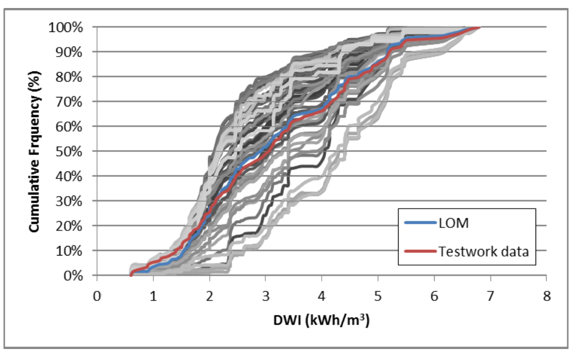
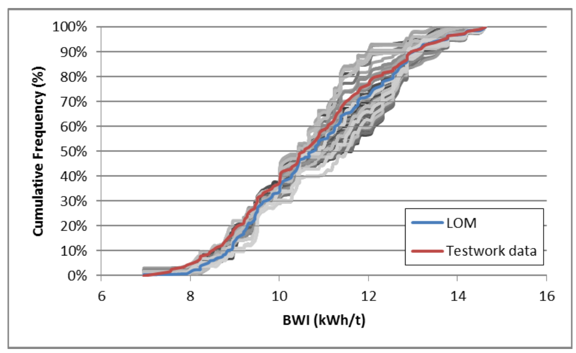


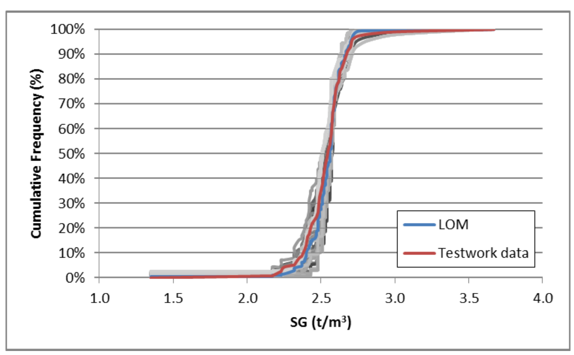
Figure 7 – Mine schedule according to ore types.



(a) DWI



(b) BWI



(c) SG

Figure 5 – Cumulative frequency of DWI, BWI and SG values.

The inputs for the Monte Carlo simulations were then set by replacing uncertain values (i.e. variables such as DWI, BWI and SG) in the Ausgrind model with the weighted probability distribution functions defined previously. These functions simply represent a range of different possible values that a variable could take instead of limiting to just one or a few cases.

Additionally, the distribution of the comminution parameters (e.g. SG x competency x hardness) were correlated individually and in a time series (i.e. according to the mining schedule). These correlations coefficients were defined in matrices, as illustrated in Figure 6, for a multi-period range that contained a set of comminution parameter distributions in each mining period.

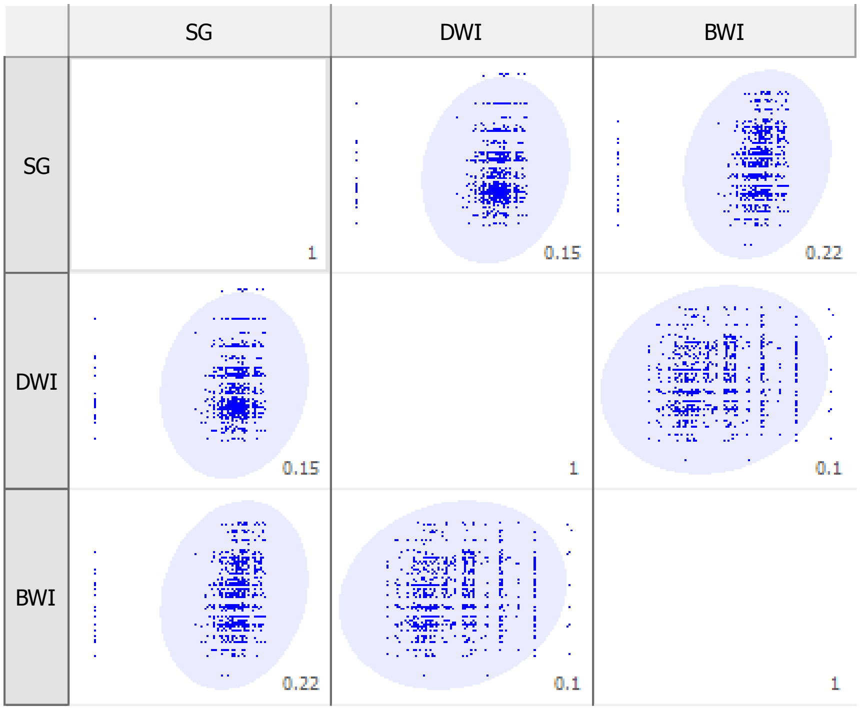
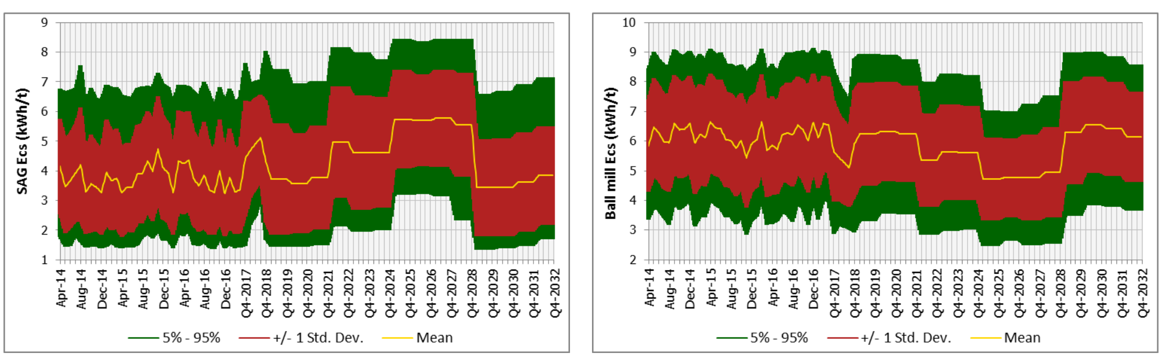


Figure 6 – Correlation matrix between SG, DWI and BWI values.

The model outputs (SAG mill Ecs and ball mill Ecs) were recalculated thousands of times during the simulation. Each time, it sampled random values from the distribution functions defined for each input, placed them in the Ausgrind model, and recorded the resulting outcome. The result of the simulation is an overview of a whole range of possible SAG and ball mill specific energy outcomes calculated for a final product size (P80) of 150 microns, including the probabilities of occurring as shown in Figure 7.



(a) (b)

Figure 7 – SAG and ball mill specific energy predictions.

These simulations revealed an increase in SAG specific energy after years 7 and 9, which was mostly related to an increase of ore type “J”. Therefore, only the first 7 years of mine life were included in the analysis because mitigating the risks associated with competent rock in the end of mine life may not be economical. After year 7 or 9, additional capital (e.g. secondary crushing) or operating cost (e.g. high intensity blasting) expenditures can be made to mitigate that risk.

Two different levels of contingency for the design criteria were compared: the typical 80th percentile (P80) and alternate cases based on the mean value plus one SD (+1SD). Additionally, a few comparative Ausgrind calculations were conducted using other methods to analyze the comminution dataset and establish the design criteria. These were compared against the proposed comminution design method using risk analysis. The different criteria are described as follows and the obtained SAG and ball mill specific energy requirements for design are presented in Table 6.

1. The 80th percentile ore properties (input) were used to calculate a single output (i.e. SAG and ball mill).
2. The SAG and ball mill Ecs (output) were calculated for each testwork sample (input) and the 80th percentile of the output was selected.
3. The average of the 80th percentile values of yearly weighted ore properties distributions (input) were used to calculate the SAG and ball mill Ecs (output).
4. The average of the 80th percentile of yearly weighted SAG and ball mill Ecs distributions that had originally been calculated in case 2 (output).
5. The average of the 80th percentile of the Monte Carlo simulations (output).
6. The mean +1SD ore properties (input) were used to calculate the SAG and ball mill Ecs (output).
7. The SAG and ball mill Ecs were calculated for each testwork sample and the mean +1SD of the output was selected.
8. The average of the mean +1SD of yearly weighted ore properties distributions (input) were used to calculate the SAG and ball mill Ecs (output).
9. The average of the mean +1SD of yearly weighted SAG and ball mill Ecs distributions that had originally been calculated in case 2 (output).
10. The average of the mean +1SD of the Monte Carlo simulations (output).

Table 6 – SAG and ball mill Ecs for different design criteria.

Case	**SAG mill Ecs (kWh/t)**	**Ball mill Ecs (kWh/t)**	**Contingency**	**Data Used**	**Weighted Data**
1	6.2	6.2	P80	input	no
2	6.3	7.5	P80	output	no
3	5.3	6.9	P80	input	yes
4	5.2	8.0	P80	output	yes
5	5.3	7.7	P80	output	yes
6	6.3	6.3	+1SD	input	no
7	6.3	7.3	+1SD	output	no
8	5.5	6.9	+1SD	input	yes
9	5.5	7.9	+1SD	output	yes
10	5.5	7.8	+1SD	output	yes

The results show that the use of P80 and +1SD contingencies are generally equivalent for this dataset. However, the contingency when applied to the output data rather than the input data, increased the ball mill Ecs. This occurred because the Ausgrind output had already accounted for individual correlations of DWI and BWI, reflecting the effect of low competency ore when estimating the SAG and ball mill Ecs. Using the mine schedule to weight the data, either input or output, resulted in a reduction in the SAG mill

Ecs mainly because the increase in the amount of more competent ore (J) after year 7 was intentionally neglected.

The results also revealed that applying the contingency on the weighted model output data (i.e. cases 4 and 9) was almost equivalent to running the Monte Carlo simulation (i.e. cases 5 and 10). However, the outcome of the Monte Carlo simulation is believed to be slightly more realistic in terms of power balance, as the actual variabilities and correlations were properly accounted for.

The required mill equipment was then sized using the Ausgrind design tool for two different criteria – case 6 (traditional approach) and case 10 (Monte Carlo). The selected mills for each case are presented in Table 7.

Table 7 – SAG and ball mill equipment selected for different design criteria

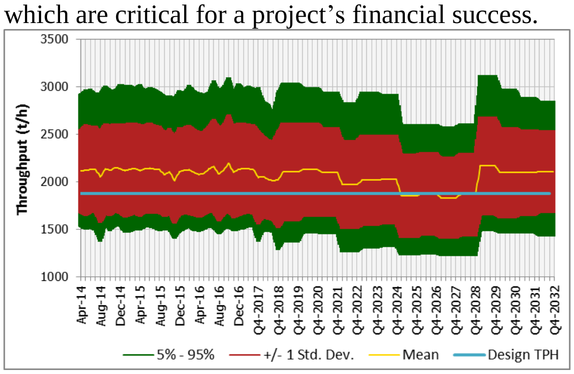
Design Parameters	unit	Case 10		Case 6	
		SAG Mill	Ball Mill	SAG Mill	Ball Mill
Number of mills	-	1	1	1	1
Dimensions (D x EGL)	ft	32 x 19	26 x 39	36 x 19.5	24 x 39
Specific energy, Ecs[1]	kWh/t	5.7	7.6	6.4	6.2
Mill speed	%Cs	75	75	75	75
Ball charge	%	12	30	12	30
Total charge	%	26	30	26	30
Nom. Pinion power	kW	10,700	14,200	12,100	11,500
Max. Pinion power	kW	12,800	15,700	13,800	12,800
Installed power	kW	13,000	16,000	14,000	13,000

[1]Ausgrind adjusts the SAG specific energy to reflect the design mill geometry and operating conditions. The ball mill Ecs is then adjusted accordingly

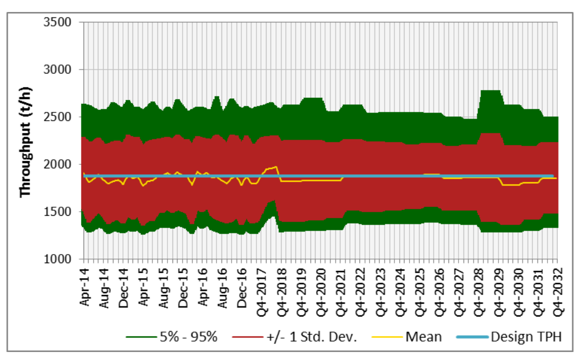
Throughput Risk Analysis

Lastly, a risk analysis simulation was conducted to estimate the throughput variability for each design case, as presented in Figure 8. The results show that the case 6 design has higher chance of not achieving design throughput (1875 t/h at 8000 h/y) than case 10. These simulations required product size of 150 microns, and case 6 was ball mill limited at 82 % of the time, and case 10, 59 % of the time. Hence, higher throughput figures could be achieved if the circuit was set up so that cyclone underflow could report to SAG mill feed or if a coarser grind size was viable.

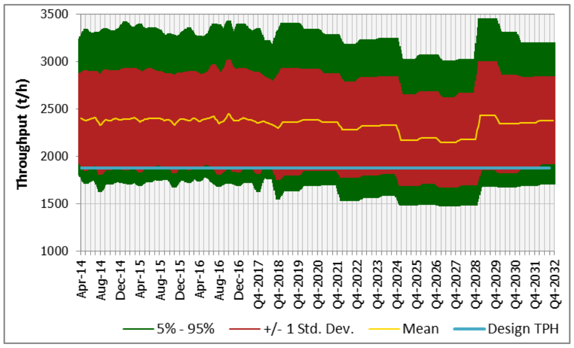
In conclusion, the case 10 design can be validated once the mill selected using this criteria has a good chance of meeting the required throughput and grind size, especially in the first seven years of LOM which are critical for a project's financial success.



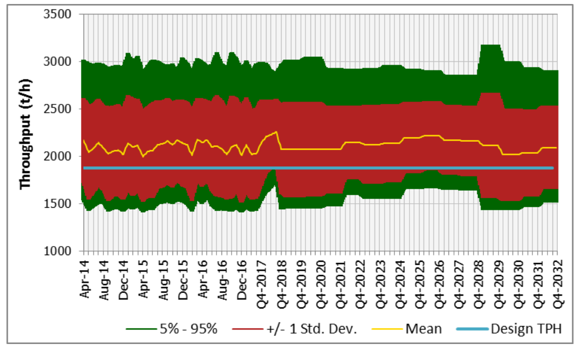
Case 10 at nominal operating conditions



Case 6 at nominal operating conditions



Case 10 at maximum operating conditions



Case 6 at maximum operating conditions

Figure 8 – Throughput variability for design cases 6 and 10 at nominal and maximum operating conditions.

CONCLUSIONS

The following conclusions can be drawn from this paper:

- It is well recognized in the literature that no single criterion is ideal to select a reliable design point.
- The source of the data needs to be examined and understood to select criteria that are believed to be prudent design points.
- The present work described a simple and robust method that relies on simulation techniques to identify and quantify risks associated with feed variability in comminution circuit design.
- The simulations provide a reliable description of all probable specific energy requirements over time. They can be used to make informed decisions on design criteria.
- The level of contingency adopted to establish the design criteria is based the project owner's appetite for risk and other associated project factors.
- The method accounts for correlations between competency and hardness. This important feature facilitates obtaining the correct power split in SAB/SABC circuits.
- The ability to define the likelihood of achieving throughput and/or grind size over time can be used to identify potential risks and make accurate decisions as to whether or not accept a particular design.
- Ultimately, there is a trade-off between risk and reward that will be covered in a follow-up paper.

ACKNOWLEDGEMENTS

The authors would like to acknowledge Ausenco for supporting this development and allowing it to be presented at the SAG conference in Vancouver. Tim Napier-Munn from the Julius Kruttschnitt Mineral Research Center and Matt Pyle from Ausenco are also acknowledged for their advice on statistics and Monte Carlo simulation. We also wish to thank Eddie McLean from Ausenco for editing the paper.

REFERENCES

Amelunxen, P., Bennett, C., Garretson, P. & Mertig, H. (2001). Use of geostatistics to generate an orebody hardness dataset and to quantify the relationship between sample spacing and the precision of the throughput predictions. In Barratt, D. J., Allan, M. J., Mular, A. L. (Eds.), *International Autogenous and Semiautogenous Grinding Technology*. Vancouver: University of British Columbia (UBC).

Amelunxen, P., Mular, M.A. Vanderbeek, J., Hill, L. & Herrera, E. (2011). The effects of ore variability on HPGR trade-off economics. In Major, K., Flintoff, B. C., Klein, B., McLeod, K. (Eds.), *Proceedings of the International Autogenous and Semi-autogenous Grinding and High Pressure Grinding Roll Technology*. Vancouver: University of British Columbia (UBC).

Barratt, D. J. & Allan, M. J. (1986). Testing for autogenous and semiautogenous grinding: a designer's point of view, *Minerals and Metallurgical Processing*, 65– 74.

Bergholz, W. S. & Schreder, M. L. (2004). Escondida – Phase IV Grinding Circuit. In Proceedings 36th Annual Meeting. The Canadian Institute of Mining, Metallurgy and Petroleum.

Bond, F. C. (1961). Crushing & grinding calculations part I, *British Chemical Engineering*, 6:378–385.

Bulled, D. (2007). *Grinding circuit design for ADANAC Moly Corp using a geometallurgical approach* (SGS Technical Paper No. 2007-01). Retrieved from http://www.sgs.com/minerals

Burgess, D. (2012). A method of calculating autogenous/semi-autogenous grinding mill specific energies using a combination of Bond work indices and Julius Kruttschnitt parameters, then applying efficiency factors. In *Proceedings of the 11th Mill Operators' Conference* (pp. 37–44), Hobart. AusIMM.

Dagbert, M. & Bennett, C. (2006). Domaining for geomet modelling: a statistical/geostatistical approach. In Allan, M.J., Major, K., Flintoff, B. C., Klein, B., Mular, A. L. (Eds.), *International Autogenous and Semiautogenous Grinding Technology* (pp. 426-4340). Vancouver: University of British Columbia (UBC).

Daniel, M. & Wang, E. (2014). Benefits of developing site specify SAG mill throughput model. In Yianatos, J., Doll, A., Gomez, C. & Kuyvenhoven, R. (Eds) XXVII International Mineral Processing Congress, Santiago. Santiago: Gecamin.

David, D. (2013a) Is an 80th Percentile Design Point Logical? Metallurgical Plant Design and Operating Strategies. In Pollard, D. & Dunlop, G. (Eds.), *Proceedings of MetPlant 2013: Metallurgical Plant Design and Operating Strategies* (pp. 6-12). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

David, D. (2013b). Geometallurgical guidelines for miners, geologists and process engineers – discovery to design. In Dominy, D. (Ed.), *Proceedings of the Second AusIMM International Geometallurgy Conference 2013* (pp. 129-132). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Deutsch, C. V. (2013). Geostatistical modelling of geometallurgical variables – problems and solutions. In Dominy, D. (Ed.), *Proceedings of the Second AusIMM International Geometallurgy Conference 2013* (pp. 7-15). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Dobby, G., Bennett, C. & Kosick, G. (2001). Advances in sag circuit design and simulation applied to the mine block model. In Barratt, D. J., Allan, M. J., Mular, A. L. (Eds.), *International Autogenous and Semiautogenous Grinding Technology* (pp. 221-234). Vancouver: University of British Columbia (UBC).

Dobby, G., Bennett, C., Bulled, D. & Kosick, X. (2004). Geometallurgical modeling - the new approach to plant design and production forecasting/planning, and mine/mill optimization. In *Proceedings of the 36th Annual Canadian Mineral Processors Conference*, Ottawa.

Flores, L. (2005). Hardness model and reconciliation of throughput models to plant results at Minera Escondida Ltda., Chile. In *Proceedings of the Canadian Mineral Processors* (pp 301–324). The Canadian Institute of Mining, Metallurgy and Petroleum.

Hunt, J., Kojovic, T. & Berry, R. (2013). Estimating comminution indices from ore mineralogy, chemistry and drill core logging. In Dominy, D. (Ed.), *Proceedings of the Second AusIMM International*

Geometallurgy Conference 2013 (pp. 173-176). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Keeney, L. & Walters, S. G. (2011). A Methodology for Geometallurgical Mapping and Orebody Modelling. In Dominy, D. (Ed.), *Proceedings of the First AusIMM International Geometallurgy Conference 2013* (pp. 217-225). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Keeney, L., Walters, S. G. and Kojovic, T. (2011). Geometallurgical Mapping and Modelling of Comminution Performance at the Cadia East Porphyry Deposit. In Dominy, D. (Ed.), *Proceedings of the First AusIMM International Geometallurgy Conference 2013* (pp. 73-83). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Kittler, P., Liebezeit, V., Ehrig, K. Macmillan, E. & Lower, C. (2011). 'It Seemed like a Good Idea at the Time …' Common Mistakes in Geometallurgy. In Dominy, D. (Ed.), *Proceedings of the First AusIMM International Geometallurgy Conference 2013* (pp. 133-138). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Kosick, G., Bennett, C. & Dobby, G. (2002). *Managing company risk by incorporating the mine resource model into design and optimization of mineral processing plants* (SGS Technical Paper No. 2002-21). Retrieved from http://www.sgs.com/minerals

Lane, G. S., Foggiatto, B. & Bueno, M. P. (2013). Power-based Comminution calculations using AusGrind. In Alvarez, M., Doll, A., Kracht, W. & Kuyvenhoven, R. (Eds.), *Proceedings of the 10th International Mineral Processing Conference – PROCEMIN 2013*. Santiago: Gecamin.

McInnes, C. Dobby G. & Schaffer, M. (2002). *The application of ceet and fleet in the base metals industry: current status and future vision* (SGS Technical Paper No. 2002-20). Retrieved from http://www.sgs.com/minerals

Morrell, S. (2004). Predicting the specific energy of autogenous and semi-autogenous mills from small diameter drill core samples. *Minerals Engineering*, 17 (2004):447–451.

Morrell, S. (2009). Predicting the overall specific energy requirement of crushing, high pressure grinding roll and tumbling mill circuits. *Minerals Engineering*, 22 (2009):544–549.

Morrell, S. (2011a). The appropriateness of the transfer size in AG and SAG mill circuit design. In Major, K., Flintoff, B. C., Klein, B., McLeod, K. (Eds.), *Proceedings of the International Autogenous and Semi-autogenous Grinding and High Pressure Grinding Roll Technology*. Vancouver: University of British Columbia (UBC).

Morrell, S. (2011b). Mapping orebody hardness variability for AG/SAG/crushing and HPGR circuits. In Major, K., Flintoff, B. C., Klein, B., McLeod, K. (Eds.), *Proceedings of the International Autogenous and Semi-autogenous Grinding and High Pressure Grinding Roll Technology*. Vancouver: University of British Columbia (UBC).

Napier-Munn, T. J., Morrell, S., Morrison, R. D. & Kojovic, T. (2005). *Mineral comminution circuits: their operation and optimisation*. Julius Kruttschnitt Mineral Research Centre: Brisbane.

Shaw, W. J., Khosrowshahi S. & Weeks, A. (2013). Modelling geometallurgical variability – a case study in managing risk. In Dominy, D. (Ed.), *Proceedings of the Second AusIMM International Geometallurgy Conference 2013* (pp. 247-252). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Siddall, B. & Putland, B. (2007). Process design and implementation techniques for secondary crushing to increase milling capacity. In *SME Annual Meeting*. Preprint 07-079. SME: Salt Lake City.

Stark, S. Perkins, T. & Napier-Munn, T. J. (2008). JK Drop Weight Parameters – a statistical analysis of their accuracy and precision, and the effect on SAG mill comminution circuit simulation. In *Proceedings of MetPlant 2008: Metallurgical Plant Design and Operating Strategies* (pp. 147 – 156). Perth: Australasian Institute of Mining and Metallurgy (AusIMM).

Starkey J. & Dobby, G. (1996). Application of the Minnovex SAG Power Index at five Canadian SAG plants. In Mular, A. L., Barratt, D. J. and Knight, D. A. (Eds.) *Proceedings of the International Conference on Autogenous and Semi-Autogenous Grinding Technology* (pp. 345–360). Vancouver: University of British Columbia (UBC).

Starkey, J., Hindstrom, S. & Nadasdy, G. (2006). SAGDesign testing – what it is and why it works. In Allan, M. J., Major, K., Flintoff, B. C., Klein, B. and Mular, A. L. (Eds.) *Proceedings of the International Conference on Autogenous and Semi-Autogenous Grinding Technology* (pp. 240–254). Vancouver: University of British Columbia (UBC).

Williams, S. R. (2013). A historical perspective of the application and success of geometallurgical methodologies. In Dominy, D. (Ed.), *Proceedings of the Second AusIMM International Geometallurgy Conference 2013* (pp. 37-47). Carlton: Australasian Institute of Mining and Metallurgy (AusIMM).

Wirfiyata, F. & Mccaffery, K. (2011). Applied geo-metallurgical characterisation for life of mine throughput prediction at Batu Hijau. In Major, K., Flintoff, B. C., Klein, B., McLeod, K. (Eds.), *Proceedings of the International Autogenous and Semi-autogenous Grinding and High Pressure Grinding Roll Technology*. Vancouver: University of British Columbia (UBC).