TESTWORK VARIABILITY – IMPLICATIONS FOR GRINDING CIRCUIT DESIGN

*T. G. Vizcarra[1], B. Wong[1]

[1]JKTech Pty Ltd

40 Isles Road, Indooroopilly, QLD, Australia, 4068

(*Corresponding author: t.vizcarra@jktech.com.au)

Abstract

JKTech has completed a comparative testing program of Bond tests as an addition to its "round-robin" quality control program for JK Drop Weight (JKDW) and SMC tests. Over seventy Bond tests of representative splits of quarry material were undertaken by over thirty participating laboratories. To JKTech's knowledge, this represents the largest comparative study of Bond testing reported in the literature.

The scale of the exercise meant that the variability due to systematic differences between laboratories, as well as the inherent experimental error of the test, could be decoupled. These "errors" in the Bond test are often under-appreciated in design, and the results are discussed in the context of implications for mill sizing. Other major factors that drive ball milling efficiency, which are not accounted for by the Bond equation but are strongly evident in the JKTech database, are also presented.

Keywords

Design risk, Bond test, variability

Introduction

In a recent publication, Weier and Chenje (2018) reported the results of comparative Bond testing undertaken by over 30 metallurgical laboratories located around the world. JKTech undertakes this type of quality control program regularly for the JKDW and SMC tests (which measure crushing and SAG milling "hardness"), but in the most recent exercise, laboratories were also given the opportunity to participate in a wide-scale Bond testing comparison.

The study is reported in detail in Weier and Chenje (2018), but a summary of the methodology used is as follows:

- 500 kilograms (kg) of material from a local quarry (in south-east Queensland, Australia) was sourced by JKTech and crushed to 100% passing 3.35 millimetres (mm). Material from this quarry has historically been used by JKTech for round-robin testing as it is considered to be mineralogically and texturally homogeneous and thus likely to minimise unwanted variability in comminution testing.
- This material was progressively split into 5 kg sub-samples that were then bagged and treated as comparative testing program samples. Each laboratory was requested to follow their standard Bond test procedures with a 150 micron (µm) closing screen, and to undertake the tests in duplicate.
- Bond Work indices (BWi) in kilowatt hours per tonne (kWh/t) were then reported back to JKTech.

After the exclusion of several results that failed to meet basic quality assurance/quality control (QA/QC) standards, the final dataset consisted of 72 Bond test results on the same material. To JKTech's knowledge, this represents the largest comparative study of Bond testing reported in the literature. Further analysis of the previously reported results has been undertaken, and is discussed in the context of how to better appreciate, and in turn manage, the risks associated with grindability testing in the context of ball mill design.

Decoupling and Managing Bond Test Variability

A dot-plot of the BWis is shown in Figure 1. The mean BWi was 15.4 kWh/t, and the overall standard deviation (SD) 1.1 kWh/t. Individual test values ranged from 12.8 kWh/t to 17.9 kWh/t, the range of 5.1 kWh/t being 33% of the mean of 15.4 kWh/t. This is a large variation that has serious implications for design and mill sizing, but the immediate question that arises is: how much of this variability stems from the inherent reproducibility of the test, compared to systematic differences in procedure and test conditions between the labs?

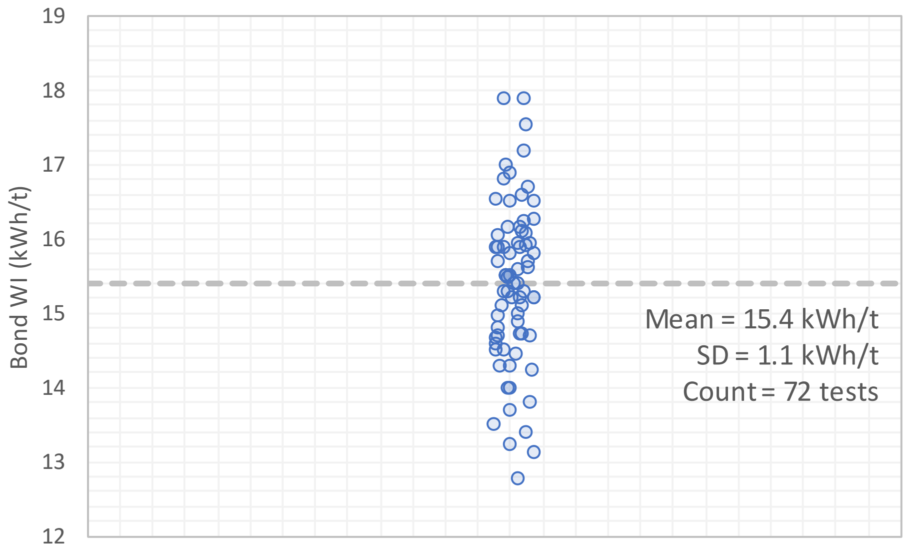

Figure 1 – Dot-plot of 72 Bond test results reported by participating laboratories

A simple one-way analysis of variance (ANOVA, Table 1) can isolate these sources of variability (Napier-Munn, 2014). The MS_{error} term = 0.14 $(kWh/t)^2$, and equates to the variance due to experimental error, independent of the variabilities arising from the labs. The square root of this reflects the SD due to pure error, which is 0.37 kWh/t. This represents an error of 2.5%, relative to the mean BWi of 15.4 kWh/t.

Table 1 – ANOVA results of round-robin Bond testwork

Source of Variation	SS	df	MS	F	P-value
Between labs	79.7	35	2.28	16.1	$1.28e^{-13}$
Error	5.1	36	0.14		
Total	**84.8**	**71**			

Hence, if a design engineer was to subject replicate samples to Bond testing at a single lab of choice, the reported BWis could be expected to align very closely. The 95% confidence intervals on the reported mean from a single laboratory can be calculated using $\pm\, ts/\sqrt{n}$ (where $t_{36\ df} = 2.0$, s = 0.37 kwh/t, n = 2 repeats per laboratory) = ± 0.5 kWh/t. This indicates that the Bond test is, perhaps somewhat surprisingly, a reproducible test, as long as there is consistency in the choice of laboratory (and presumably in the technician executing the test). This is illustrated in Figure 2, which shows that, with only a few exceptions, duplicate values measured by each lab were very consistent.

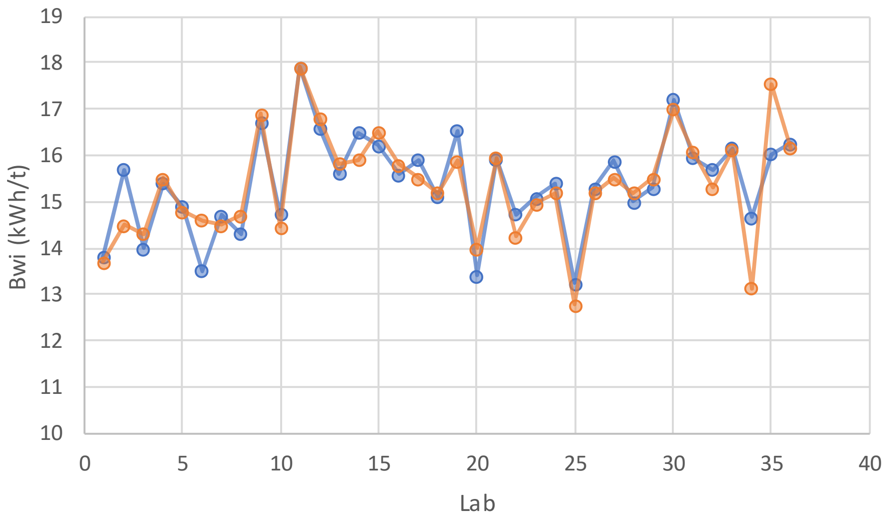

Figure 2 – Comparison of duplicate BWi values reported by each laboratory

The total testwork variability illustrated in Figure 1 was therefore dominated by systematic differences between the labs, confirmed by the small P-value in the ANOVA table to be statistically highly significant. It is these differences which must be managed if a "true" BWi is required with a certain degree of confidence, as opposed to if only relative changes in BWi are necessary to be discerned.

Short of visiting labs, auditing their procedures, and ensuring that testwork conditions are within the strict limits of the test (Napier-Munn, Morrell, Morrison, & Kojovic, 1996), the only way to obtain any degree of confidence in a sample's "true" BWi is to obtain its average value reported by a cross-section of laboratories. The question then arises: to how many labs should the design engineer send representative splits of the sample of interest?

The answer is dependent on the overall SD of the data (a good estimate of which has been quantified in this study, 1.1 kWh/t) relative to the degree of confidence that is desired in the result. Figure 3 shows the number of measurements required to obtain 95% confidence intervals (CI) of different magnitudes calculated from:

$$n = \left(\frac{z\sigma}{m}\right)^2 \qquad (1)$$

n = sample size

z = 1.96 for 95% confidence

σ = expected sample SD

m = desired margin of error (CI) in kWh/t.

If a 95% CI of ± 1.3 kWh/t is deemed acceptable, then only three different labs are required. If a 95% CI of ± 1 kWh/t is required, then this increases to five different labs. For a 95% CI of ± 0.5 kWh/t, then close to 20 labs must be tested, which would be considered impractical in commercial applications.

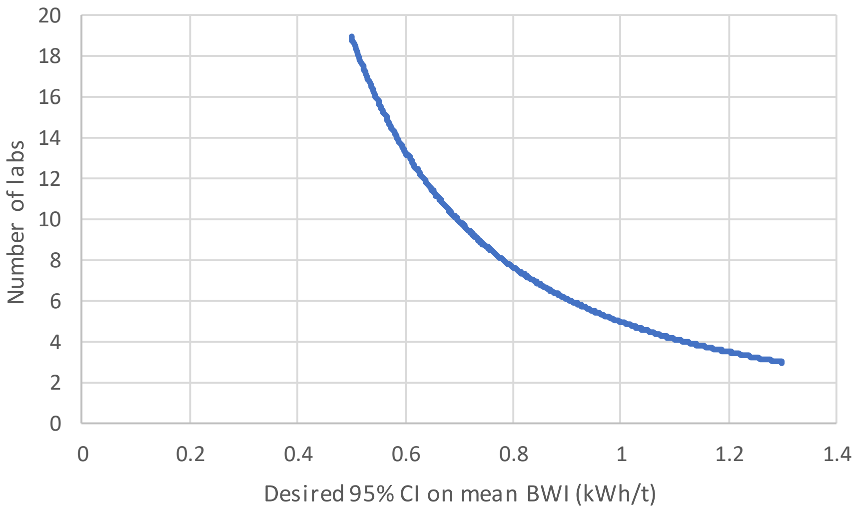

Figure 3 – Number of labs required to achieve ± 95% confidence intervals of different magnitudes for a mean BWi value

However, the benefits of using an average BWi calculated from even a small number of labs, as opposed to a single BWi measurement, cannot be overstated. Figure 4 shows a comparison between the distribution of single BWis (i.e., the same distribution as that shown in Figure 1, but represented as a histogram), against the distribution of 10,000 average BWis each calculated from sampling with replacement from the round-robin dataset (each of the 10,000 samples was of size = 3). It can be seen that the distribution of means is narrower (SD = 0.6 kWh/t, compared to 1.1 kWh/t), illustrating that the value of an average BWi is associated with more confidence compared to a single measurement, as intuition would suggest, and has a better chance of being a good representation of the "true" BWi of the sample.

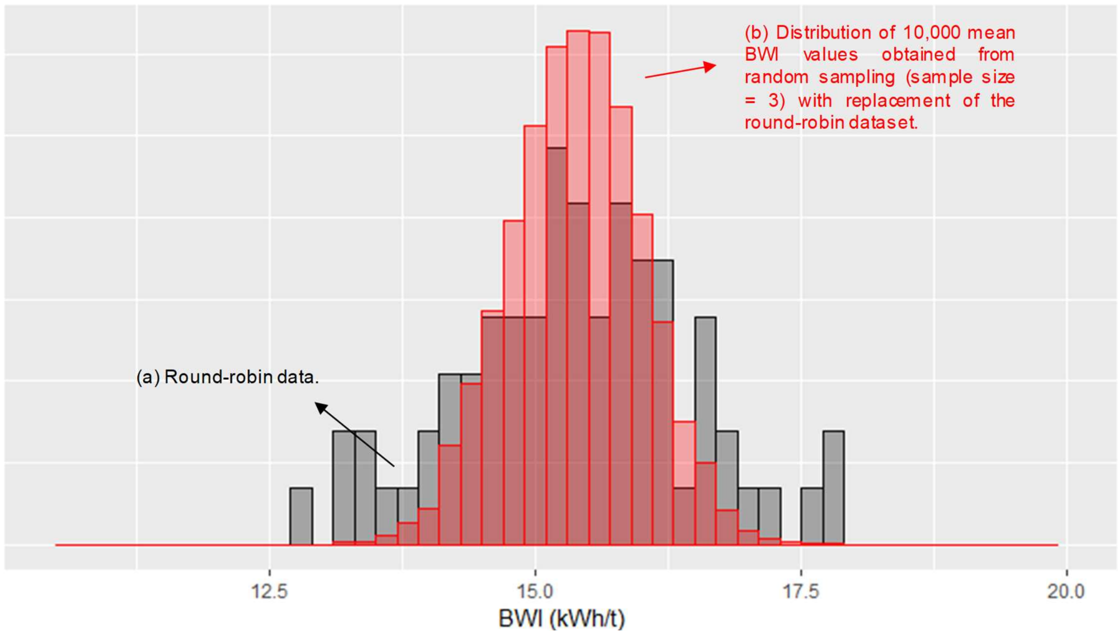

Figure 4 – Comparison of (a) distribution of single BWi measurements from this study; and (b) distribution of mean BWi values constructed from 10,000 sample means each of size = 3

Implications for Design

The BWi measured in a laboratory is frequently used to obtain an estimate of ball milling power requirements. Different mill vendors, EPCMs and consultants often have models, developed from internal databases, that calculate the necessary power that a ball mill should draw in order for it to undertake its intended duty. While the merits of using the Bond approach to size ball mills in modern SABC circuits has been previously debated (Morrell, 2011), for simplicity, the basic Bond equation is used here to illustrate the consequences of the uncertainty of a BWi:

$$Ball\ mill\ circuit\ specific\ power\ at\ the\ pinion\ \left(\frac{kWh}{t}\right) = 10\ BWI\ \left(\frac{1}{\sqrt{P_{80}}} - \frac{1}{\sqrt{F_{80}}}\right) \qquad (2)$$

A Monte Carlo simulation was undertaken to represent the range of possible power requirements resulting from the uncertainty in a calculated BWi average. The 10,000 BWi means represented in Figure 4(b) were used to obtain 10,000 possible power draw requirements that could be calculated by a design engineer, depending on the sample of three BWi measurements used to estimate the ore grindability. A typical circuit F_{80} (1.6 mm) and P_{80} (106 µm) were chosen. A target circuit throughput of 500 t/h was also chosen. The pinion power was converted to motor input power assuming it to be 93.5% of motor input power, typical for a gearbox and pinion system. While mill motors are rated based on their output power, the results are compared to JKTech's database which details motor input powers of mills that have been surveyed by JKTech over the years (discussed later).

The range of motor input power requirements, according to Bond, is shown in Figure 6. A mean power draw requirement of 5939 kW is predicted. But, depending on the sample mean that was used (each sample was of size = 3), a design engineer could have also arrived at power draw requirements of between 5474 kW and 6405 kW 95% of the time, a range of approximately 1 MW. The implications for the final mill sizing are dependent on the level of design risk that can be tolerated.

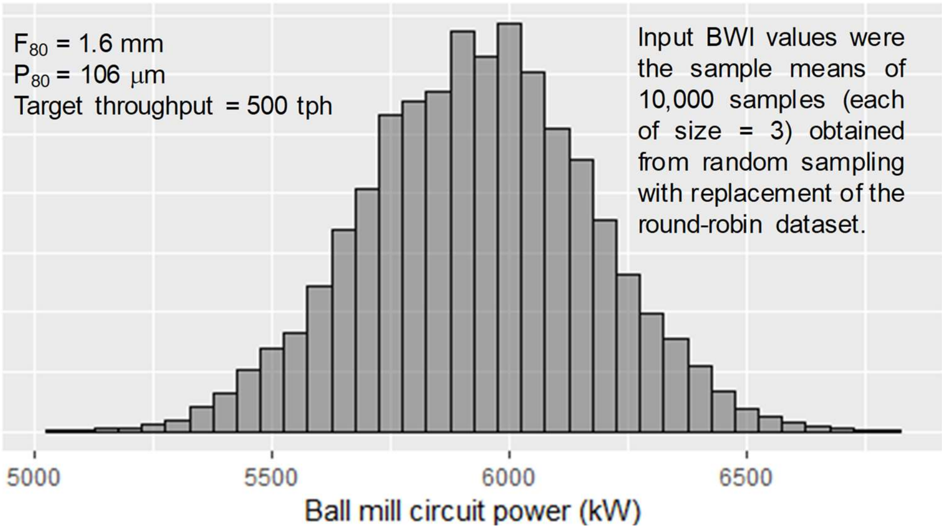

Figure 5 – Example spread of ball milling power requirements (calculated with the Bond equation) resulting from normal lab-to-lab experimental error in the BWi test

JKTech Experiences

The distribution of possible ball milling power illustrated in Figure 6 was calculated using the classical Bond equation. In practice, JKTech's experience to date is that the variability in mill power requirements, given the uncertainties in a BWi result, are not as severe as shown in Figure 6. This is because, in addition to the BWi, there are other process and design variables apparent in the JKTech database that affect milling efficiency, but which are not acknowledged in the Bond equation.

JKTech has encountered a wide variety of ball mill designs, ore types, and circuit and operating conditions over the years. This necessitates the use of statistical methods to disentangle the effect of each competing variable in the database, allowing them to then be quarantined and trended in isolation using regression models. Some examples are shown in Figure 6. It can be seen that mills with longer lengths, for instance, have generally been observed to be less efficient compared to mills of equivalent power draw but with larger diameters (i.e., high length/diameter aspect ratio mills are less efficient). For milling density, a clear minimum is observed at 73% to 74% solids. It must be emphasised that this is a global minimum in the database, which does not otherwise have the granularity to predict, for instance, the effect of changes in slurry rheology due to the presence of clays in the feed. However, it does reflect typical operational experience, in that slurries that are excessively dilute or dense will inhibit grinding performance, and that a milling density "sweet spot" should be targeted.

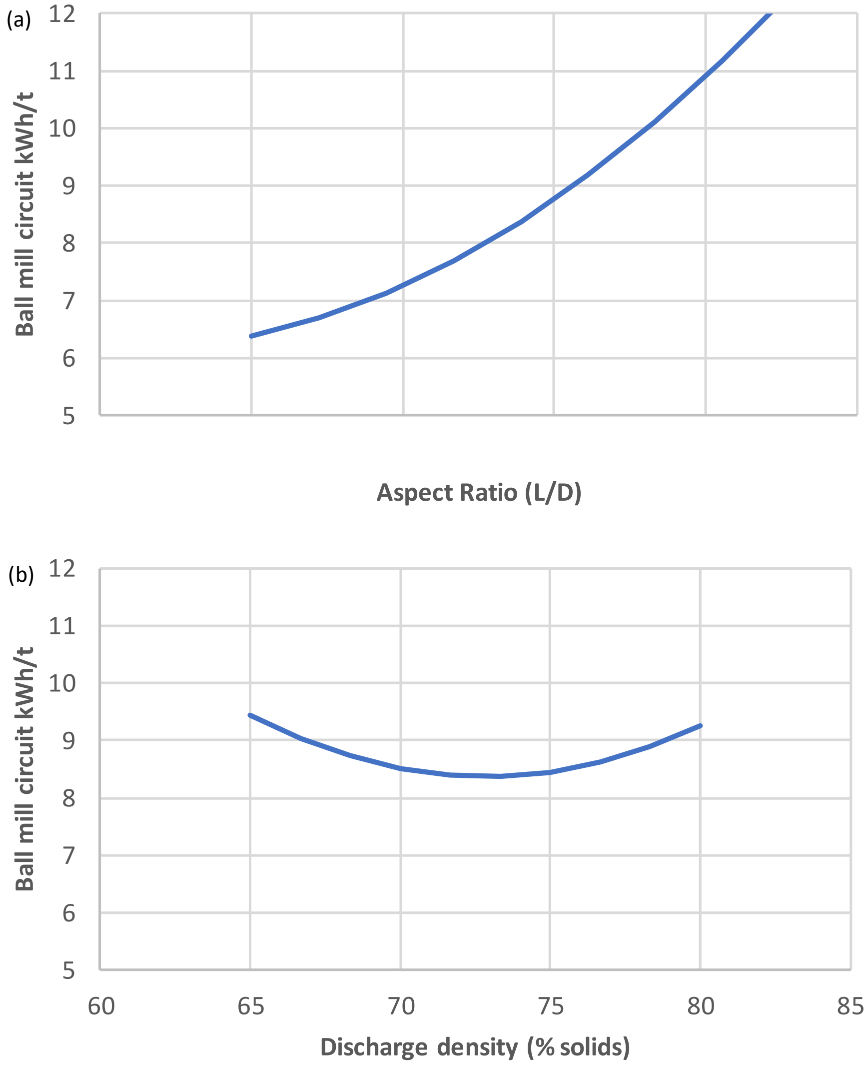

Figure 6 – Example predictions from the JKTech database regression showing the effect of (a) ball mill aspect ratio (values have been redacted); and (b) discharge % solids, on ball milling efficiency. Trends were generated with P_{80} and BWi held at constant values

The impact of BWi uncertainty predicted by the database appeared somewhat tempered, compared to Bond predictions. Figure 7 shows the same distribution of Bond power requirements previously illustrated in Figure 5, but this time compared with the corresponding distribution predicted by inputting the broad range of 10,000 BWi means shown in Figure 4(b), into the JKTech database regression (for which typical mill aspect ratio and milling % solids inputs were assumed and held constant for the comparison). While shifted to a lower mean value of 5553 kW, the distribution is also narrower, indicating that, at least in JKTech's experience to date, the impact of the uncertainty in BWi is not as severe as that compared to Bond predictions, although it is still generally under-appreciated in design.

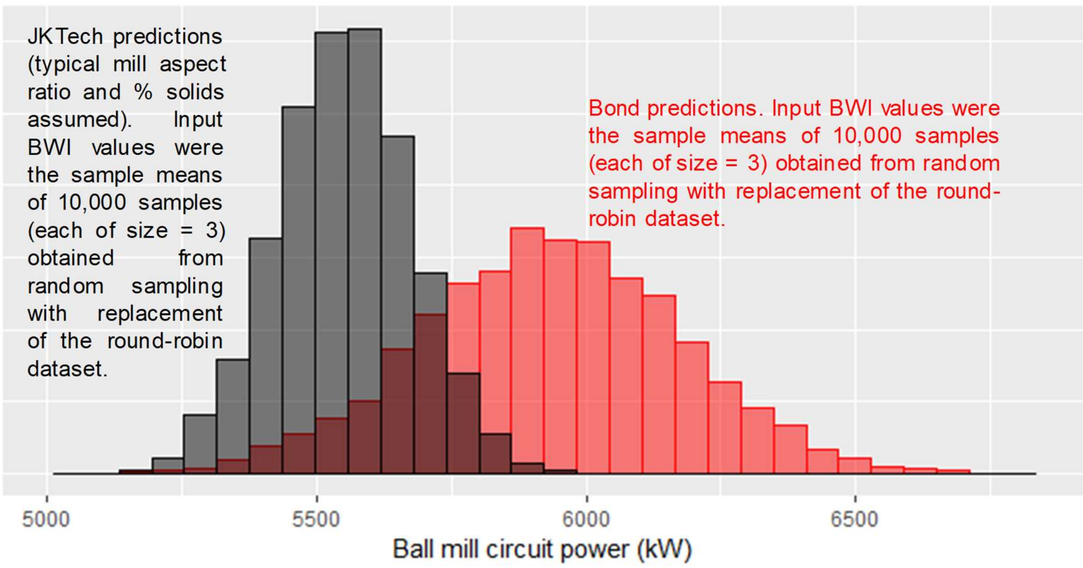

Figure 7 – The effect of inputting 10,000 possible mean BWi values from Figure 4 into the Bond equation (red histogram) upon possible power draw calculations for a 500 t/h ball milling circuit (F_{80} = 1.6 mm, P_{80} = 106 µm). Also shown is a comparison with the range of power draw requirements predicted by inputting the same 10,000 mean BWi values into the JKTech database regression (black histogram)

It must be emphasised that the discussion in this paper has been limited to the effect of Bond testwork variability on mill sizing. Other relevant issues that have been discussed by other authors include different modelling and specific power calculation philosophies (Bailey, Lane, Morrell, & Staples, 2009), as well as geological variability and how to manage that risk in greenfield and operational projects (Jackson & Young, 2016).

Conclusions

Comprehensive round-robin testing of over 30 metallurgical laboratories shows that the experimental error of the Bond test is, surprisingly, quite small. Systematic differences in Bond test results between laboratories, however, can be problematic. These real differences have implications for ball mill sizing that must be recognised, however, they can also be managed by undertaking repeat tests across laboratories to mitigate uncertainty and obtain more confidence in a Bond test result.

Acknowledgements

The authors wish to thank JKTech for permission to publish this paper. Prof. Tim Napier-Munn and Greg Lane are gratefully acknowledged for useful comments and feedback in the preparation of this manuscript.

References

Bailey, C., Lane, G., Morrell, S., & Staples, P. (2009). What can go wrong in comminution circuit design? *Tenth Mill Operators' Conference*. Adelaide, SA: AusIMM.

Jackson, J., & Young, M. F. (2016). Ore type – everything to someone but nothing to anyone. *Proceedings of the Third AusIMM International Geometallurgy Conference (GeoMet) 2016*. Perth, WA: AusIMM.

Morrell, S. (2011). The appropriateness of the transfer size in AG and SAG mill circuit design. *Fifth International Conference on Autogenous and Semiautogenous Grinding Technology*. Vancouver, British Columbia.

Napier-Munn, T. J., Morrell, S., Morrison, R. D., & Kojovic, T. (1996). *Mineral comminution circuits: Their operation and optimisation.* Indooroopilly, Queensland: Julius Kruttschnitt Mineral Research Centre, University of Queensland.

Napier-Munn, T. J. (2014). *Statistical methods for mineral engineers: How to design experiments and analyse data.* Indooroopilly, Queensland: Julius Kruttschnitt Mineral Research Centre, University of Queensland.

Weier, M. L., & Chenje, T. (2018). Accuracy of the Bond ball mill test and its implications. *14th International Mineral Processing Conference & 5th International Seminar on GeoMetallurgy.* Santiago, Chile: Procemin-Geomet 2018.