Predicting Mill Ore Feed Variability Using Integrated Geotechnical/Geometallurgical Models

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ABSTRACT
The Ban Houayxai mine (BHX) is a relatively low-grade, low-cost, open pit gold-silver deposit in Laos operated by Phu Bia Mining, a subsidiary of PanAust. The ore production rate at BHX is 4.5 Mt/a, with direct tipping to a semi-autogenous grinding/ball mill circuit with a carbon-in-leach process plant. Approximately 100 000 oz of gold is produced per annum.

The operation is located in mountainous terrain with minimal run-of-mine stockpiling. This results in limited capacity for blending from stockpile, with the mill instead reliant upon direct feed ex-pit. Since commissioning in 2012, the plant has seen significant variation in milling rates due to variability in the feed properties of the oxide, transition and primary ores. As part of an ongoing continuous improvement program, an integrated approach was initiated, focusing on maintaining and enhancing production in the future as the proportion of harder primary ore increases. This will specifically focus on direct blending from the loading face using the ore properties and blast fragmentation to maintain mill throughput.

This approach was based on the concept of physical assets management, commencing with improving information and knowledge of the condition of the orebody through modelling the characteristics, variability and performance of the feed for processes relevant to throughput. These models are used to support both mine and process plant production planning.

The key ore feed characteristics and parameters modelled for the life-of-mine are blastability index, powder factor, crushability or impact resistance and grindability. These predictive spatial models were based on the data from diamond drill holes used in resource definition and geotechnical drilling programs by integrating geotechnical, geological, geochemical and metallurgical data.

At the early stages of implementation, the models are being utilised for ore blending decisions to provide guidance and support for budgeting, long-term mine planning, blast design for mill feed and providing the mill with an expectation of performance.
predictive spatial modelling of key parameters related to throughput for the life-of-mine (LOM). These key parameters are the feed size and mill hardness in terms of crushing and grinding.

The predictive models are based on the data from diamond drill holes used in resource definition and geotechnical drilling programs by integrating geotechnical, geological, geochemical and metallurgical data types, together with the associated lithological model. The key parameters modelled are:

- blastability index (BI), index of the ease to blast the rock mass and the required powder factor (pF) for a constant mean fragmentation size using empirical engineering models
- crushability or resistance to impact breakage (A*b) through a relationship between the geotechnical rock mass rating (RMR), the intensity of weathering/oxidation and A*b from metallurgical SMC tests
- grindability, the Bond ball mill work index (BWi), through relationships between lithology, geochemistry, intensity of weathering/oxidation and BWi metallurgical tests.

Due to the data types and sampling density, the models of these parameters are a combination of differing levels of granularity and resolution. They are not considered a precise reflection of reality, but show likely spatial and performance variability, allowing options and controls to be considered in maintaining or enhancing production in a proactive manner.

At the early stages of implementation, the models are being utilised to provide guidance and support for budgeting, long-term mine planning, blast design for mill feed and providing the mill with an expectation of performance.

**Physical asset management**

The standard definition of asset management is ‘the systematic and coordinated activities and practices through which an organisation optimally and sustainably manages its assets, their associated performance, risks and expenditures over their life cycle to achieve the strategic plan’ (BSI Group, 2008; Woodhouse, 2011). Although historically the management of physical assets is strongly associated with equipment maintenance, this concept can and has been extended to other physical assets such as oil reservoirs or mineral deposits. Some companies within the oil and gas industry, particularly...
BP and Shell, adopted this approach during the mid to late 1990s, resulting in large improvements in project value, such as 17 per cent increased output at 50 per cent lower operating costs, rather than the business as usual case of chasing efficiency gains through doing the same thing quicker and cheaper (Woodhouse, 2010). Elements that enable successful asset management include: clear direction and leadership, cross functional coordination, staff awareness, competency and commitment and, importantly, adequate information and knowledge of asset condition, performance, risks and costs and the interrelationship between these.

The approach adopted at BHX is a scaled down concept of the asset management system that focuses on the aforementioned enabling elements in relation to throughput mine production forecasts and the associated mine life cycle plan only. As shown in Figure 2, the concept can be divided into four components: predict, control, react and monitor.

The first component, predict, develops models of the expected conditions and performance of the orebody, including spatial variability. This includes the rock properties and process attributes associated with the key process, such as blasting, crushing and grinding within the block model. The prediction of performance is developed under constrained conditions for each block, and is not treated as a deterministic outcome but as aid in the next component.

The second component, control, is where engineering solutions to manage or optimise the predicted performance are developed together with management plans. This may include solutions such as blending, scheduling, alternative blast designs, processing conditions or simply nothing. As all of the predictive models are estimates with uncertainty, there will still be a need for reacting to unplanned/unexpected issues that could not be predicted. But rather than dominating the operation, the focus switches to proactive prediction and control with monitoring and review as a feedback loop.

Modelling and use of the models
There are many perspectives of models in the literature (Giere, 2010; Knuuttila, 2011). The standard view is that a model directly represents an object. However, here we take the more pragmatic perspective in that an agent intends to use the model to represent part of the world for some purpose, so it is the agent that specifies which similarities are intended and for what purpose (Giere, 2010; Cunningham, 2005). Thus, the success of a model depends not only on the direct accuracy of representation to the real world, particularly given limitations on spatial resolution, input data and process descriptions, but also on the purpose for which the model is employed. In this case, the model needs to satisfy a distinct purpose: an improvement of the current method in spatially and temporally predicting the key rock properties and the associated performance under constrained conditions for use by many agents, including mine planners, metallurgists, blasting engineers and geologists.

BAN HOUAYXAI MINE GEOLOGY AND OPERATIONS
BHX is a structurally-controlled epithermal gold-silver deposit hosted within an early Permian volcano-sedimentary sequence of the Trong Son Fold belt in the south-western extremity of the Phu Bia Contract Area (Manaka et al., 2014).

The deposit is located on a steep narrow north–south oriented ridge that protrudes into the Nam Ngum 2 Reservoir, a recently filled hydroelectric scheme. As at the end of 2013, the published Mineral Resource at BHX stood at 64 Mt at 0.90 g/t Au and 7.1 g/t Ag for a total of 1.8 Moz Au with Ore Reserves of 36 Mt at 0.81 g/t Au and 8.0 g/t Ag (Aust, 2014).

Gold and silver mineralisation occurs as structurally-controlled narrow veins and disseminations and within the volcano-sedimentary sequence. The most commonly mineralised veins are quartz-pyrite±carbonate±electrum±native silver veins with wall rock alteration of sericite, chlorite and adularia hosted (Manaka et al., 2014; Brost, 2011). The disseminated mineralisation is predominately associated with silicification of the feldspathic sandstone with higher grades in breccias. At least three phases of deformation have been imposed on the deposit, resulting in a significant structural complexity in shearing, faulting, fracturing and jointing.

The LOM plan comprises three pits – north, central and south – with a LOM stripping ratio of 1.5:1. Due to the topography, space is at a premium, meaning that the operation is a direct tip operation into the primary crusher with only a very small
stockpile capacity. The process plant consists of a 26 ft 6.5 MW SAB mill circuit feeding a conventional CIL circuit.

Three ore types have been defined at BHX based on the weathering profile: oxide, transitional and primary. Average throughputs were assigned to these ore types based on test work within the feasibility study and during construction/commissioning, and they are a critical component of planning, scheduling and forecasting. However, since commissioning, the variability in throughput has been high, both in terms of amplitude and period, due to the mix of the ore types and the variability within them.

PREDICTIVE MODELLING APPROACH

The approach to the predictive modelling initially consists of decisions as to:

- which key parameters are to be predicted
- what methodology is to be applied to predict key parameters and potential performance
- what input variables are suitable and relevant
- the domaining methodology for each of the variables
- the spatial modelling methodology for each variable and parameter.

These decisions are based on the type, quantity and quality of available data and the purpose of the models to improve and support mine and process plant production planning. These decisions are often interrelated, and are developed iteratively.

Methods for the prediction of the key parameters include:

- direct tests, including small-scale tests
- empirical ‘engineering’ models
- empirical ‘proxy’ models – where a relationship is established between variables or proxies and parameters from a limited set of direct tests.

In an ideal world, the most relevant, direct tests and measurements of the key parameters would be undertaken at a sample density relevant to their spatial variability and spatially modelled. However, for geotechnical and geometallurgical parameters, this is rarely the case as direct measures of a parameter are often problematic, and the logistics, cost and time of obtaining and processing the relevant data is significant. Hence, the empirical engineering and proxy models are the more common. These models require the input of many disparate data types at varying sample intervals and density with varying sensitivities, and thus the final outputs are multilayered and consist of a mix of levels of model granularity and resolution. It is our preferred approach to spatially model the primary input variables with the appropriate methodologies, where possible, and then apply the empirical models to predict the parameters (response) rather than vice versa. This approach better matches the spatially modelling methodology to the data (Coward et al, 2009).

Domaining is a first order decision that partitions the data set into spatially coherent, geological and statistically acceptable ‘domains’ (Coombes, 2009; Vann, 2008). Some prior knowledge of the key parameters is required to identify the geological drivers of the parameter’s variability and performance that can be related back to the drill hole. However, as this isn’t always possible, other domaining options should be considered. Domaining methods include:

- value- or grade-based – the domains are based on selected cut off values
- population-based – the domains are defined on downhole zones that are statically similar
- generic geological-based – the domains are based on geological units or model (eg lithology/alteration)
- process/variable geological driver-based – the domains are based on the differing casual geological drivers of the parameter’s performance.

For practical purposes, the predictive models are required to have spatial representation within a block model. For this initial model, a number of the input variables were spatially modelling using relatively simple linear estimation approaches. Although the block model implies a certain level of granularity, this is not always the case, and an understanding of the underlying data and model limitations is required.

Key parameters

The key ore-related parameters relevant to throughput for the BHX circuit are the size distribution of the feed to the mill and the comminution or mill hardness.

The feed size is a function of the fragmentation from blasting and primary crushing. Rather than predicting the feed size, the approach taken is to predict the ease of which the rock breaks due to blasting (BI) and the required energy or pF to achieve a constant mean fragmentation to the mill using empirical rock mass and fragmentation ‘engineering’ models.

The parameters relating to mill hardness consist of crushability and grindability. As the milling circuit at BHX is an SAB circuit, the key comminution parameters are crushability using the Julius Kruttschnitt A*b derived from SMC tests and grindability using the BWI derived from the Bond ball mill test (Napier-Munn et al, 1996; Morrell, 2004). The approach to predicting these is via an empirical proxy model for the BWI and a combination of empirical ‘engineering’ and proxy models for the A*b, as will be discussed later.

Data set

The data set used for the predictive models included the 330 diamond resource definition drill holes with a nominal drill spacing of 50 x 25 m and 49 geotechnical drill holes. A number of data types were available as potential inputs into the models, including geological logging and models, geotechnical logging and testing and geochemistry and metallurgical testing. The main data types associated with these drill holes are shown in Table 1. Other data types used included:

<table>
<thead>
<tr>
<th>Data table</th>
<th>Key data types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collars</td>
<td>East, North, relative level, length</td>
</tr>
<tr>
<td>Survey</td>
<td>Depth, azimuth, dip</td>
</tr>
<tr>
<td>Lithology</td>
<td>Lithology, weathering, texture and deformation</td>
</tr>
<tr>
<td>Alteration</td>
<td>Supergene type/mode/intensity, alteration type/mode/ intensity</td>
</tr>
<tr>
<td>Assays</td>
<td>Au, Ag, Zn with selected intervals assayed for a wide range of multi elements</td>
</tr>
<tr>
<td>Point load</td>
<td>Core size, caliper, IS, MPa, failure on new or pre-existing structure, structure type, estimated uniaxial compressive strength</td>
</tr>
<tr>
<td>Geotech</td>
<td>Rock quality designator (RQD per cent), number of sets, strength, fracture frequency</td>
</tr>
<tr>
<td>Structure</td>
<td>Structural type, orientation and roughness</td>
</tr>
<tr>
<td>Veining</td>
<td>Type and intensity</td>
</tr>
<tr>
<td>Mineralisation</td>
<td>Oxide and sulfide minerals and quantity</td>
</tr>
</tbody>
</table>
• 3D geology and grade models
• pit design stages
• geotechnical reports, including uniaxial compressive strength (UCS) tests
• comminution test results, including SMC tests for A*b and BWI, mineralogy and point load tests.

BLASTABILITY INDEX AND POWDER FACTOR MODELS

The approach adopted for the modelling of the pF is based on Cunningham’s empirical Kuz-Ram fragmentation model (Cunningham, 1986, 2005). This estimates the mean fragmentation (X) that would result from a known energy factor used in specific rock mass conditions. Reworking of the model results in the estimation of the required energy pF to achieve a mean fragmentation (X), as shown in Equation 1. For BHX, analysis of mill and comminution test results data indicated that a mean fragmentation of 150 mm was appropriate for ore.

\[
\text{Required Powder Factor (kg/m}^3) \ pF = \left( \frac{X}{\left( A + Q^{0.167} \right) \left( RWS^{0.633} \right) } \right)^{-1.25} \\
(1)
\]

The inputs into the Kuz-Ram model are:

- \( X \) = mean fragmentation diameter
- \( Q \) = mass of explosive per blasthole
- \( RWS \) = relative weight strength of the explosive
- \( A \) = rock factor – specific rock mass conditions

The rock factor, \( A \), is used to take into account variations in rock mass conditions. This can be related to Lilly’s BI through a simple multiplication factor of 0.12 (Lilly, 1986, 1992; Widzyk-Capehart and Lilly, 2001). The BI model is shown in Equation 2:

\[
BI = 0.5 \times \left( JPS + RMD + JPO + RDI + S \right) \\
(2)
\]

The inputs into the BI are:

- \( JPS \) = joint plane spacing rating
- \( RMD \) = rock mass description rating
- \( JPO \) = joint plane orientation rating
- \( RDI \) = rock density influence
- \( S \) = rock strength

The JPS and RMD ratings are derived from the fracture frequency data, with the JPO rating derived from the orientation of structures in relation to the final pit design. RDJ expresses the influence of the density of the rock, while \( S \) is a function of the UCS that was estimated from point load data. An overview of the data quantity and quality of the input variables of fracture frequency, structure, density and point load for the relevant inputs into the BI are outlined in the following section.

The BI and pF estimates were calibrated for BHX through blasting studies that were in progress as the model was developing.

Inputs

Joint plane spacing rating and rock mass description rating

The level of fracturing within the resource development holes was recorded as the number of fractures per drill run, which was then converted to fractures per metre. Analysis indicated that the distribution of fracture frequency (FF) was very similar for all lithologies, indicating that lithology is not a control on fracturing, nor could the existing structural model explain the fracture distribution. Therefore, the domain method selected was population-based, utilising the CuSum statistical method for zoning the data based on changes in the data using a 5 m composite length down the drill hole (Keeney and Walters, 2011). The zones were then clustered into groups based on the mean and standard deviation for each of the zones to create five spatially coherent FF domains. For the initial model, the FF was interpolated into the block model using inverse distance weighting (IDW) methodology from which the JPS and RMD rating was derived.

Joint plane orientation rating

The structural database is dominated by data for veining, which accounts for some 53 per cent of the data followed by foliation and joints at 18 per cent. The structural analysis of joints and faults/shears indicated that both have similar orientations and are lithology independent. However, there is a significant difference in orientation between the northern and central pit areas. The northern pit is dominated by those dipping steeply to the WNW–NW, whereas the majority in the central pit dip steeply to the ENE–NE.

A total of 12 structural regions were defined based on the analysis of the structural orientation against the slope and orientation of the final pit design. Within the spatial model, each block within these regions was assigned a JPO rating based on the dominant orientation in relation to the pit wall design using Lilly’s rating system.

Rock strength

As part of the geotechnical studies, a limited number (two to five) of UCS tests were conducted on each of the main six lithologies. This data indicates a large variation and overlap in UCS for the lithologies, with ranges from 30–160 MPa.

The database also contained single break point load data on drill core corrected to 50 mm drill core(Is). Point load tests are commonly used as an indirect test to predict UCS (ASTM International, 2008). Although there were some 20 000 point load results in the database, each was a single point break. Over 50 per cent were recorded as failing on a pre-existing defect and, of the remaining, only 1180 did not record an associated defect. Thus, in order to obtain a representative indication of in situ rock strength, a more detailed analysis was undertaken by only considering the data where the point load tests had not failed on a pre-existing structure, were diametral tests, the fracture frequency (FF/m) was less than two and rock was fresh/primary. This resulted in a significantly reduced data set where individual lithologies were grouped based on their distribution of point load estimated UCS.

A total of seven lithological-based rock strength groups resulted in three groups of volcanic lithologies with an average estimated UCS of 75, 80 and 175 MPa, and four groups of sedimentary lithologies with an average estimated UCS of 50, 80, 125 and 175 MPa. Similar investigations based on a combination of alteration with and without lithology did not identify distinct populations of rock strength, suggesting that lithology was a key geological driver. Due to the limited data and the simplified 3D lithological model, rock strength was assigned to the block based on the average estimated UCS for that lithology. The conversion factor from estimated UCS to the S rating was increased to improve the calibration between the predicted BI and pF to the site blasting studies. The estimates of UCS do not take into account any anisotropy or rock strength at scales larger than drill core (Pierce, Gaida and Degange, 2009).
Rock density influence
As some 66,000 bulk density measurements were obtained from the drilling data set using the calliper method, there was sufficient data for interpolation of the densities into the block model. The domaining of this data was based on lithology with interpolation by IDW followed by the conversion to the RDI using the standard BI rating system.

Mass and relative weight strength of explosive
The inputs for the mass of explosive per blasthole (Q) and the relative weight strength of the explosive (RWS) were kept constant at 165 kg/hole and 95 respectively. These were based on assumptions of the blast engineering design with respect to drill hole diameter, stemming height and explosive characteristics for a 10 m bench height.

Results
The application of Equations 1 and 2 to the inputs at block level resulted in the estimated BI and pF. Over the LOM 65 per cent of the ore is estimated to need pFs between 1.3 and 1.9 kg/m$^3$ to achieve an X50 fragmentation of 150 mm (Figure 3). The results for the primary ore suggest that 53 per cent of the ore requires a pF greater than 1.6 kg/m$^3$.

On a yearly basis from the current mine plan, 2015 and 2018 are expected to require the most blasting energy, with the model predicting that ten per cent of the ore requires a pF less than 1.3 kg/m$^3$ and 25 per cent greater than 1.9 kg/m$^3$. For 2017 and 2020, the estimates are 40 per cent and ten per cent respectively.

An example of the spatial variability of the BI and pF for the north and centre pits at the 570 m level is shown in Figure 4. The BI is shown for both ore and waste within the pit design, whereas the pF X150 mm is shown for ore blocks only. The relatively short range and large amplitude variability in both BI and pF can be observed in the northern pit, suggesting that achieving a constant size distribution will be difficult. While the centre pit appears to have less spatial variability with larger, more consistent zones, it is likely that blast areas will straddle some of these boundaries.

COMMINUTION MODELS
The approach to predict the common measures of crushability and grindability, A*b and BWi respectively, is through empirical proxy models. Relationships are identified and developed between A*b and BWi from ‘training’ data sets and commonly logged or measured aspects of drill core such as geological logging and assays. Thus, analysis of the training data set is required with the aim of identifying geological drivers and related variability to the A*b and BWi parameters.

Analysis of comminution data set
The initial comminution test work consisted of 32 drill core composites ranging in intervals from 4–17 m. These represented material from within the yearly production periods 2013–2015, and were tested by SMC and bond ball mill tests. The results from a further 25 samples were added to the data set later in the project to represent material from production periods 2015–2020. The data showed a wide range in both impact resistance and grindability, as shown in Figure 5. The impact resistance as indicated by A*b ranged from a very hard 25 to a soft 118, although the majority were between 30 and 55. Similarly, grindability as indicated by the BWi ranged from 10–35 kWh/t, with the majority between 15 and 27 kWh/t.

No clear relationships in terms of the distribution of A*b and/or BWi was identified with geological aspects logged from the drill core such as weathering, lithology, alteration, alteration intensity, veining or combinations of these. The best correlation was between A*b and BWi themselves, together with density.

The point load data was not considered due to:
• the point load from the drill core was very poorly correlated with the comminution parameters due to the low representivity of the point load measurements from the drill core relative to the composite length of the comminution samples
• the issues around the quality of the point load data as outlined in the previous section.
In an attempt to understand the geological drivers, whole rock X-ray fluorescence (XRF) and quantitative X-ray diffraction (QXRD) mineralogy was obtained for the comminution data set. In terms of A*b, the XRF geochemistry showed poor correlations, with no element >0.2. From the QXRD data, mica correlated best with A*b at 0.4. The better correlations to BWi from the QXRD data were again mica (-0.43) followed by chlorite/chlorite/kaolin and calcite (0.1–0.2), and from the XRF data set, Ba, K and Na at only 0.2. The correlations improved when the data set was partitioned by the logged supergene type (oxidation), with correlation coefficients increasing to up to 0.75 in the case of Mn and Mg for supergene type SLE (completely oxidised) and OSM partially oxidised, mixed oxides after sulfides). The variables with correlations >0.3 (either positive or negative) are outlined in Table 2. This suggests that oxidation and mineralogy (relating to subtle hydrothermal alteration) have an influence on the comminution parameters.

A*b
As the standard geological drivers of A*b parameters could not be determined through modelling, using the geological-based variables such as lithology or assays was not possible. Hence, an alternative approach was sought.

The crushability of a sample is a function of the physical properties of the rock, which includes rock strength and the quantity and quality of any fractures or discontinuities. Together with the correlations with FF and density for A*b, this pointed towards the possibility of rock mass aspects having a significant influence on the parameter. A standard method of rating rock mass is through Bieniawski’s empirical RMR (Bieniawski, 1976, 1989; Karzulovic and Read, 2009). The parameters and calculation of the RMR is:

\[
RMR = SIR \text{ rating} + RQD \text{ rating} + DS \text{ rating} + CD \text{ rating} + GW \text{ rating}
\]

where:
- \( SIR \) = strength of intact rock
- \( RQD \) = rock quality designation
- \( DS \) = spacing of discontinuities
- \( CD \) = conditions of discontinuities
- \( GW \) = groundwater

The approach firstly calculates the RMR for the data set at block level, followed by an adjustment factor based on supergene unit to create the comminution rock mass rating (CRMR). The CRMR is then related to A*b from the SMC tests via regression to create a predicted A*b. The model was created using a subset of the A*b data from the comminution data set.

**Inputs**

The SIR is a rating based on the estimated UCS, with the DS rating based on FF. As discussed earlier, both of these are inputs in the BI, with the only difference being that the
TABLE 2
Summary of correlations of Bond ball mill work index (BW\textsubscript{i}) and A*b with X-ray fluorescence whole rock geochemistry and quantitative X-ray diffraction mineralogy.

<table>
<thead>
<tr>
<th>Supergene type</th>
<th>SLE</th>
<th>OSM</th>
<th>SEC</th>
<th>PRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>BW\textsubscript{i}</td>
<td>Mg, Mn, P, K</td>
<td>Mn, Mg, Fe, Si</td>
<td>Ba, K</td>
<td>Mn, Si</td>
</tr>
<tr>
<td>Density</td>
<td></td>
<td></td>
<td>Density, fracture frequency</td>
<td></td>
</tr>
<tr>
<td>Zn, Ag, S</td>
<td>Zn, S</td>
<td></td>
<td></td>
<td>Ag, Zn, S</td>
</tr>
<tr>
<td>A*b</td>
<td>K, Mn, Mg</td>
<td>P, Mn</td>
<td>Fe, K, S, P (0.35)</td>
<td>Fe</td>
</tr>
<tr>
<td>Density</td>
<td></td>
<td></td>
<td>Fracture frequency</td>
<td></td>
</tr>
<tr>
<td>Zn</td>
<td>Zn, S</td>
<td></td>
<td>Fracture frequency, density</td>
<td></td>
</tr>
</tbody>
</table>

SLE = completely oxidised; OSM = partially oxidised, mixed oxides after sulfides; SEC = transition zone with consistent presence of sulfides with iron oxides; PRI = primary with no oxidation.

RMR rating system was applied as compared to the BI rating system. The RQD rating is based on the RQD measurements and, similarly to the FF, a population-based approach using the CuSum method and manual clustering into five domains based on the mean and standard deviation of the zones. For this initial model, the FF was interpolated into the block model using the IDW methodology to which the RMR rating system was applied.

CD is a function of the roughness of structures that is derived from core logging using the International Society of Rock Mechanics Suggested Methods and the Australian Standard AS 1726-1993 with the roughness classified by Stepped, Undulating and Planar together with Rough, Smooth or Slickensides, resulting in nine categories (Phu Bia Mining, 2010). The distribution of these roughness categories varies according to lithology. Hence, the roughness rating was based on lithology, where lithologies with a significant proportion of planar structures with smooth or slickenslide structures received a lower rating compared to those dominated by stepped rough structures.

The GW rating related to the groundwater condition of the rock mass, which, for open pit mines, is assumed to be constant and damp with its associated RMR rating.

The predicted A*b versus measured A*b from all of the SMC data set and not just those used in the development data set is shown in Figure 6. The methodology provides a prediction that is practical given that the purpose of the model is to highlight regions of significant variability in A*b.

**Bond ball mill work index**

The analysis of the BW\textsubscript{i} data with respect to geological, geochemical and geotechnical variables indicated that if dominated by the oxidation/supergene, then density and FF together with Zn and Ag are the most correlated of the variables that were consistently measured across the deposit. Thus, the BW\textsubscript{i} was predicted using linear regression of combinations of these variables for each supergene type. The very high BW\textsubscript{i}s >30 kWh/t were excluded from the proxy models.

Due to the small number of samples in the SLE and OSM zones, the number of variables within the regression was limited to a maximum of two. The regression performed well for all supergene units in terms of R\textsuperscript{2} (>70); however, the SEC (transition zone with consistent presence of sulfides with iron oxides) had the largest residuals, which requires further investigation and refinement. As an example, the prediction for the primary supergene zones is shown in Figure 7.

The spatial modelling of two of the variables used in the proxy modelling of BW\textsubscript{i}, density and FF were discussed earlier as part of the BI. Silver and zinc were imported from the existing BHX resource model, which has been estimated using ordinary kriging. The regression was once again applied at block level, resulting in a predicted BW\textsubscript{i}.

**Results**

The predictive models of A*b and BW\textsubscript{i} for each supergene zone were applied to the inputs at block scale, resulting in estimates of A*b and BW\textsubscript{i} for each block that contained the relevant data. Analysis of the results indicated that for supergene zones SLE and SEC, the range of the input variables within the block model was greater than that used in the development of the regression models resulting in anomalous values. These were set to null to avoid any misinterpretation by users. Of all the parameter models, the BW\textsubscript{i} had the least confidence due to the limited development data set and variables sampled across the deposit.

The results of the predicted A*b and BW\textsubscript{i} within ore over the LOM indicates that:

- 60 per cent of the ore has an A*b of 28–45, which is considered hard to moderately hard material, with only a small proportion in the very hard category (Figure 8)
- approximately 55 per cent of the ore has a BW\textsubscript{i} greater than 20 kWh/t
- 50 per cent of the ore is estimated to have an A*b of <45 and BW\textsubscript{i} >20 kWh/t, with 14 per cent having an A*b <35 and a BW\textsubscript{i} >25 kWh/t
- approximately 50 per cent of the primary ore is predicted to have an A*b of less than 35
- on a yearly basis from the current mine plan, 2018 consists of the hardest milling ore, with 65 per cent predicted to have an A*b <35 (hard ore) and five per cent >55 (moderately soft - very soft)
- the softest ore milling conditions are expected in 2016, when only 15 per cent of the ore is predicted to have an A*b <35 (hard ore) and 40 per cent >55 (moderately soft – very soft).

An example of the spatial variability of the A*b and BW\textsubscript{i} for the north and centre pits at the 570 m level is shown in Figure 9.

Initial verification of A*b indicates that the model compares favourably with material from belt cuts over a number of days. An indicative A*b was measured with a modified rotary breakage test methodology (Shi et al, 2009).

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FIG 6 – Predicted $A^*b$ via the comminution rock mass rating versus measured $A^*b$ from SMC tests using drill core samples.

FIG 7 – Predicted Bond ball mill work index (BWi) versus measured BWi for the primary supergene zone.
Implementation of the models

At the early stages of implementation, the models are being utilised in the operation by mine planning, blasting and mill personnel.

As the models are for LOM, their main function is supporting the LOM and medium-term planning and budgeting. This not only includes mine planning per se, but also includes analysis of the likely impact of potential capital and operational improvements in the mine and mill.

However, the models are also being utilised to guide tactical operational planning. The blasting-related models, including FF, BI and pF, are providing guidance:

- as to areas at risk of producing coarse fragmentation and hence impacting on throughput
- in the identification of areas where and how the planned blast design may be modified to achieve an optimal fragmentation
- in the identification of at risk areas for interim and final walls and providing guidance for the trim blast design.

The comminution parameters are currently used to provide an indication of expected SAB mill hardness and variability. Even at this relatively coarse resolution, the information allows more proactive control in terms of throughput management within the operation.

SUMMARY AND CONCLUSIONS

The integration of geological, geotechnical and metallurgical data has enabled the development of an integrated model.
PREDICTING MILL ORE FEED VARIABILITY USING INTEGRATED GEOTECHNICAL/GEOMETALLURGICAL MODELS

of key geotechnical/geometallurgical parameters. The key parameters modelled were those that relate to the rock characteristics relevant to estimating throughput for a SAB milling circuit – blast fragmentation for feed size distribution, A*b and BWi. This has allowed the numeric and spatial variability of those rock characteristics to be mapped. In the early stages of implementation, the models are being used to support mine and production planning through:

- assessing the long-term mine plan and identifying potential improvement opportunities
- providing guidance and support for budgeting
- blast design for mill feed
- ore blending decisions.

At present, the empirical 'engineering' models for blast fragmentation are predicting the mean fragmentation under a set of assumptions and do not attempt to predict the full size distribution. Thus, blast optimisation is required to increase the proportion of the fines within the blast, which improves throughput.

In any modelling, the model is constrained by the available data. In order to overcome limitations in relating traditional data such as lithology/alteration/geochemistry to A*b, a predictive model was developed based on the RMR. The RMR is an empirical-based model to quantify rock properties relevant to geotechnical engineering applications and considers properties such as intensity and condition of fracturing, rock quality and rock strength. These properties are also relevant to the 'crushability' of a rock and therefore the RMR, together with the intensity of oxidation/weathering of the rock, was used to create a predictive model of A*b.

Further enhancements could include:

- the acquisition of data in undersampled areas
- improving the quality of key variables
- the inclusion of a confidence or uncertainty level
- understanding the impact of upscaling point-related data to blocks (support)
- the conversion of the key parameters to processing performance
- further validation/calibration against field data.

To facilitate further improvements in maintaining and enhancing production of throughput, such as direct blending from the loading face using the ore properties and blast fragmentation, a similar model is being developed with a higher granularity and spatial resolution based on grade control drilling and pit mapping.

The LOM models of mill ore feed variability are an improvement in spatially and temporally predicting the key rock properties and the associated performance at BHX and are being utilised by mine planners, metallurgists, blasting engineers and geologists.

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