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Nicholas Butel
Univesity of Queensland

Alex Hossack
Rio Tinto Coal Australia

Mehmet S. Kizil
University of Queensland

PREDICTION OF *IN SITU* ROCK STRENGTH USING SONIC VELOCITY

Nicholas Butel[1], Alex Hossack[2] and Mehmet S Kizil[1]

ABSTRACT: Uniaxial Compressive Strength (UCS) and sonic velocity correlations are used widely in the Australian coal mining industry to predict *in situ* rock strength. These models are cheap, fast and easy to produce, as well as easy to understand and have a number of practical applications in mine planning and design. The major downfall of these models is that there is a large variation in UCS values at high sonic velocities limiting their predictive ability. The aim of this research project is to improve the reliability of UCS/Sonic velocity correlations by reducing the variability in the underlying data. This is performed by identifying and eliminating sources of error affecting the data and looking at the impact of certain factors on the quality of the correlations. Results show that improved models can be obtained by filtering the datasets to remove samples with high length-to-height ratios, conglomerate or pebbly lithologies, and large sonic velocity ranges.

INTRODUCTION

Uniaxial Compressive Strength (UCS) testing is a common method for estimating *in situ* rock strength in Australian coal mines, either as a standalone measure or within one of the many rock mass rating systems. Researchers in the mining industry have been investigating alternatives to UCS testing that are cheaper and faster at predicting *in situ* rock strength (Hatherly, *et al*., 2007; Lawrence, *et al.*, 2013; Sharma and Singh, 2008). One option currently adopted in a number of Australian coal mines is to correlate sonic velocity, a geophysical measurement of compression waves travelling through rock, and laboratory UCS results to obtain an equation to predict rock strength (McNally, 1990; Oyler, *et al.*, 2010). This method has the potential to be cheaper and faster to develop compared to measured UCS modelling, and is easy to create and understand. It is also useful where rock is highly fractured and the ability to collect suitable UCS samples is difficult. The main disadvantage is the significant variability in measured UCS values for a given velocity. These models currently produce low quality correlations, which reduces their reliability for use in planning and design applications.

Prediction of UCS from sonic velocity logs has been a widely accepted practice in the Australian coal mining industry for over 20 years. The first study was conducted by McNally (1987) who derived a general expression for all Australian sites, which has been widely recognised in the mining industry. Today most mines employ site-specific correlations rather than the generalised McNally equation, which has resulted in more accurate and reliable prediction of rock strength for sites (Oyler, *et al*., 2010).

At Rio Tinto Coal Australia (RTCA), site-specific correlations have previously been created for several mines. The most recent and comprehensive analysis was performed by Stam *et al.,* (2012) at Kestrel Mine. As a result of the Kestrel investigation, correlations have been produced for all other RTCA sites (Butel, 2012). It was found that site wide models were better predictors of rock strength compared to lithotype and regional models. However, the overall quality of the correlations was below the industry standard. The low quality was due to a number of uncontrolled sources of error in the data sets. It was recommended that the sources of error in the underlying data be identified and removed from the datasets to improve the correlations.

The goal of this project is to increase the reliability of UCS/Sonic correlations for use in mine planning and design applications by reducing the amount of spread in the data. To achieve this, sources of error present in the underlying data were investigated and removed. Factors causing the spread in UCS values at high sonic velocities were investigated by filtering the datasets and creating subset correlations based on these factors. Site wide and subset correlations were compared to determine if any improvement has occurred. This analysis is performed using data from eight RTCA sites, including six operating mines and two development projects. A case study of RTCA's Hunter Valley Operations

[1] *School of Mechanical and Mining Engineering, The University of Queensland, St Lucia Qld 4072, m.kizil@uq.edu.au Tel:+61 07 3365 4499*
[2] *Rio Tinto Coal Australia, 123 Albert Street, Brisbane Qld 4000; Tel (H) +61 07 3878 7612 +M: 04 5090 6307,*

(HVO) mine in the Hunter Valley (NSW) is presented in this paper as it is the best representation of overall results from all the sites.

UCS TESTING

The UCS of an intact rock sample is the amount of compressive force per unit area applied in a single direction required to induce failure. UCS is calculated by dividing the compressive load at failure by the cross sectional area of the sample, as shown in Equation 1. The UCS test is also called the unconfined compressive test as there is no confining pressure applied to rock samples (Peng and Zhang, 2007). The uniaxial compressive test can also measure the Poisson's ratio and Young's modulus of an intact rock sample.

$$\text{UCS (MPa)} = \frac{\text{Compressive Load at Failure (kN)}}{\text{Cross Sectional Area (mm)}} \tag{1}$$

This test is carried out according to the International Society for Rock Mechanics (ISRM) suggested method ISO9001 and Australian Standards under controlled laboratory conditions (Bieniawski, *et al.*, 1979). This standard specifies that cylindrical shaped specimens of intact rock core must be compressed parallel to their longitudinal axis. Sample dimensions must be within a height to diameter ratio of 2.5-3:1 and free from discontinuities or defects to be valid. Figure 1 shows a diagram of the UCS test setup and the direction of loading.

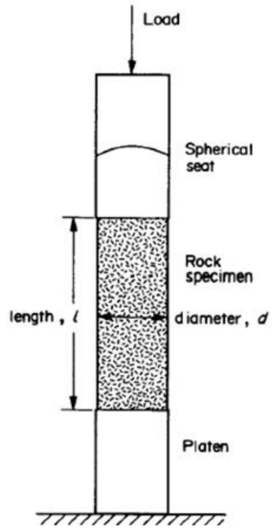

Figure 1 - Diagram of UCS test setup (Brown, 1981)

A geophysical log is a continuous record of measurements made by a probe able to respond to variations in some physical property of a rock mass (Firth, 1999). They are commonly presented as a line graph with depth on the vertical axis and the geophysical log type on the horizontal axis. Geophysical methods are divided into land and borehole, based on the location of the measurement device (Takahashi, *et al.,* 2006). Land geophysics is measured from the ground surface, while borehole geophysics places the measuring device down the borehole. Borehole geophysical methods are the focus of this discussion.

Sonic (acoustic) velocity logging is a form of borehole geophysical logging that measures the transit time of compression (P-wave) waves travelling through the rock mass surrounding the borehole (McNally, 1987). Sonic logging tools contain a transmitter which generates high frequency sound waves that travel through fluid in the borehole and rock mass in the wall. These waves are generated by an ultrasonic source, typically operating at about 20 kHz and firing at about 0.1s intervals (McNally, 1990). An uncased water or mud filled hole is required to ensure adequate acoustic coupling is achieved. These frequencies are detected by multiple receivers located on the logging tool. Measuring the time difference between arrivals at two receivers eliminates the common time spent by the signal in the borehole, leaving the time spent in the rock. This produces an interval transit time, or delta-t log. When divided by the receiver separation, the log becomes an inverse velocity or slowness log. Inverting the slowness log will produce the sonic velocity log shown in Equation 2 (Firth, 1999).

$$\text{Sonic Velocity (m/s)} = \frac{\Delta d_{Ri \to Rj} \text{ (m)}}{\Delta t_{Ri \to Rj} \text{ (s)}} \qquad (2)$$

where,

$R_{i,j}$ = Receiver i,j
Δd = distance between receivers i and j
Δt = change in time between receivers i and j detecting signal.

The most commonly used down hole sonic logging tool is the multi-channel P-wave compensated series (MS). Figure 2 illustrates the basic setup and principles of this tool. It has four receivers spaced 20 cm apart and is capable of measuring multiple sonic velocity values on four separate channels. Borehole data can be presented for 0.2, 0.4 and 0.6 m thick strata intervals on channels 1, 2 and 3 (McNally, 1990). The different velocities are determined by the change in signal times between combinations of receiver pairs. Table 1 shows the available velocity measurements on the MS2 multi-channel sonic tool. The short-spaced option, VL2F, measures the transit time between receiver 1 and 2. It is the most commonly used log in UCS/Sonic correlations, since the interval length is approximately the same as a UCS specimen, and it is least affected by spiking (McNally, 1990).

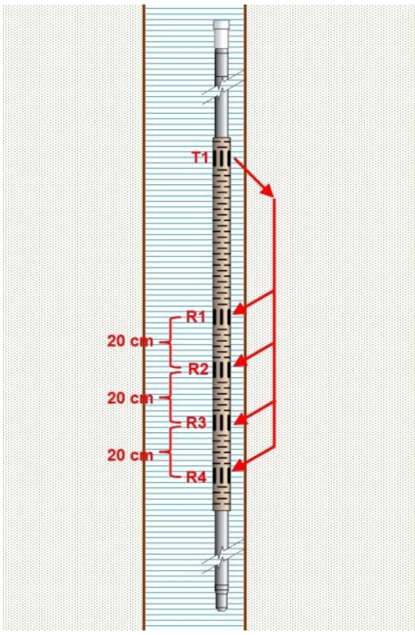

Figure 2 - MS logging tool in a water filled hole and wave propagation in the rock mass

Table 1 - Velocity logs available on a MS2 logging tool

Channel	Velocity Log	1st Receiver	2nd Receiver	Receiver Spacing
1	VL2F	R1	R2	20cm
2	VL4F	R2	R4	40cm
3	VL6F	R1	R4	60cm
4	VL2A	R3	R4	20cm

UCS/SONIC CORRELATIONS

According to Oyler *et al*., (2010) sonic logging has been routinely used for many years in Australia to obtain UCS estimates in coalfield strata. This is performed by collecting sonic log measurements of the compression P-wave velocity (m/s) and then correlating these with UCS measurements made on core samples from the same holes at the same depth. The sample points are plotted and an exponential regression line is fitted to determine the correlation for that dataset. An example of sonic velocity correlation from RTCA's Kestrel Mine is shown in Figure 3. The generalised formula for UCS/Sonic velocity correlations is shown in Equation 3. The constants *K* and *r* are derived from the regression line fitted to the data set. Only VL2F sonic velocity values are shown in this paper, although VL4F and VL2A values were also modelled but did not produce improved correlations.

$$UCS = K \times e^{a \times VL2F} \tag{3}$$

where *K* and *a* = site specific constants.

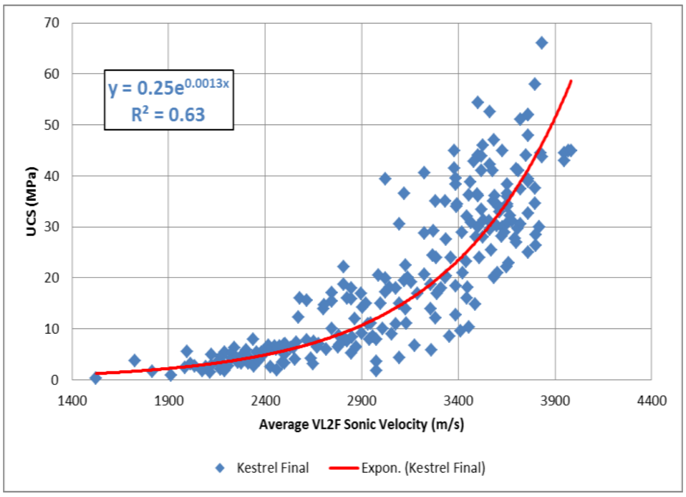

Figure 3 - Kestrel Mine UCS/Sonic correlation (Stam, *et al*., 2012)

The quality of a correlation is determined by the coefficient of determination (R^2) value, the size of the dataset, and the visual fit of the regression curve. The coefficient of determination is a measure of how well a regression curve fits a data set. This value ranges from 0 to 1, with zero showing no relationship, and one being a perfect correlation. The commonly accepted R^2 in the Australian mining industry for a good UCS/Sonic correlation is greater than 0.7 (Oyler, *et al*., 2010). This value was used as a benchmark for determining the quality of the correlations throughout this project. For descriptive purposes in this analysis, an R^2 of 0.5-0.7 is average, 0.3-0.5 is low, and <0.3 is poor quality. The minimum required dataset size to produce a reliable correlation was set at 30 sample points to assume a normal distribution under the Central Limit Theorem.

Classic studies

Research into the relationship between dynamic rock mass properties and sonic logs was first performed by Carroll (1969). He identified that there were empirical relationships between rock characteristics including Young's Modulus, shear modulus, bulk modulus and sonic logs in volcanic rocks. He recommended that this could be extended to siliceous rock types, as well as estimation of other rock parameters using sonic logs.

Based on this research, McNally conducted two classic studies, in 1987 and updated in 1990, in which sonic velocity logs and drill cores were obtained and correlated from 16 mines throughout Australia's coalfields. The first study in 1987 concluded that a single generalised correlation was sufficient for estimating *in situ* rock strength at all sites. The 1990 study indicated that these models may be lithology dependent. The findings from the 1990 study were used to predict geomechanical properties of various coal measures rock types (McNally, 1990). McNally (1987) derived a general correlation for sonic transit time and UCS, which is shown in Equation 4. This correlation has been extensively adopted in the Australian mining industry, and is still regularly quoted in literature (Oyler, *et al*., 2010; Hatherly, *et al.*, 2001; Hatherly, *et al.*, 2005).

$$\mathrm{UCS} = 1000 \times e^{-0.035t} \tag{4}$$

where,

UCS = Uniaxial Compressive Strength (MPa);
t = interval travel time of the P-wave (μs/ft).

One of the major problems identified by McNally (1987) is the level of error in the input variables, which subsequently reduces the overall accuracy of the models. He suggested that these correlations may be improved by carefully hand-picking sample locations to correspond with peaks or troughs on logs, and avoiding depths where the log gradient is steep. Samples should also be located at the centre of uniform (flat) log segments. McNally concluded that sonic logs provide a reliable and continuous record of rock strength in coal measures strata. He also commented that correlations can vary with lithology, as conglomerates appear to specifically overestimate UCS values. Sonic velocity also appears to increase with confining pressure. Importantly, he commented that sonic logs appeared not to be site-specific.

Current research

Current research in this area has separated into two schools of thought. One side supports the traditional method suggested by McNally, correlating sonic logs to UCS (Oyler, *et al*., 2010; Lawrence, 1999; Zhou, *et al.*, 2001; Stam, *et al.*, 2012; Sharma and Singh, 2008; Kelessidis, 2011; Peng and Zhang, 2007). However, other researchers suggest that this does not adequately account for variations in sonic velocity due to rock mass parameters (Hatherly, *et al.*, 2009; Medhurst, *et al*., 2010; Barton, 2006).

Sharma and Singh (2008) support the traditional theory of correlating sonic velocity directly with UCS on a regional basis. However, they believe a linear relationship is most appropriate for this relationship. Oyler *et al.* (2010) also support the use of the traditional correlation established by McNally. They created UCS and sonic travel time correlations for a number of coal mines across the USA, aimed at increasing awareness and adoption of these models in the US coal industry. It was concluded that this correlation can also be adopted in US coalfield strata to estimate UCS. According to Oyler *et al*. (2010), it is not certain that site specific correlations would give better results than a generalised model such as McNally's. They also highlighted that high-quality sonic logs are essential if the technique is to be used successfully.

A number of recent papers have identified that site-specific UCS and sonic velocity correlations produce more accurate and reliable correlations than generic models such as the McNally equation (Zhou, *et al*, 2001; Stam, *et al*., 2012; Butel, 2012). This is due to the fact that these models are able to more effectively account for variations in the local geology than generalised models. Today, mining operations are deriving their own correlations to suit local conditions. For example, at Kestrel Mine, German Creek Mine and Crinum Mine in central Queensland, where there is a well-defined and consistent geological environment, specific correlations have been derived (Zhou, *et al.*, 2005; Hatherly, *et al.*, 2009; Stam, *et al*., 2012).

Some researchers believe lithology, or rock type, specific correlations are most appropriate for *in situ* strength modelling (Lawrence, 1999; McNally, 1990). In McNally's paper in 1990, he identified that the generalised correlation curve steepens rapidly below 60 MPa UCS, indicating sonic logs are sensitive to low strength rocks. Lawrence (1999) produced linear correlations for individual rock types with reasonable success. This research indicated that the correlation gradient increases with grain size. For coarse grain rock types such as sandstone, there is expected to be a large range in rock strength values over a small range of sonic transit time. In contrast, finer grained material such as siltstone exhibits a smaller strength range, but a much larger range in sonic transit times. Peng and Zhang (2007) recognised that lithology specific models for a particular site can be effective estimators of rock strength, and that generalised lithology models across a region may produce less accurate results.

A second school of thought suggests that UCS and sonic velocity correlations are inadequate account for all of the variation in sonic velocity logs. According to this group, the broad scatter exhibited by UCS/Sonic correlations is due to the fundamental difference between static UCS and dynamic sonic log properties (Zhou, *et al.*, 2005). When the rock mass is homogenous and isotropic, sonic velocity will match the rock strength. However when structures and defects are present in the rock mass, sonic velocity can vary substantially from the UCS value due to its sensitivity to changes in conditions (Hatherly, *et al.,* 2007). This has led to the development of several alternative models to estimate *in situ* rock strength incorporating rock mass parameters influencing sonic velocity (Barton, 2006; Hatherly, *et al.*, 2007; Zhou, *et al.*, 2005; Hatherly, *et al*., 2001). These models correlate sonic velocity to rock mass properties such as rock quality, joints or fractures per metre, rock composition, or a combination of these with varying degrees of success.

The main alternative model to McNally's generalised UCS/Sonic correlation is the Geophysical Strata Rating (GSR) developed by Hatherly *et al*., (2005). It is derived solely from geophysical log data to develop a more complete strata characterization than the UCS/Sonic correlation (Hatherly, *et al.*, 2009). It is designed to provide a measure of strata properties on a linear scale from 0 to 100. The model takes into account moisture sensitivity, bedding and other factors besides rock strength (Oyler, *et al*., 2010). This model was developed using data from the Australian coalfields, so it is suited to coal measures rock types at depths less than 500 m. The major problems associated with this model are the amount of input data required and the processing involved. Purchase of the required software and training is also required. However, this model is showing signs of acceptance in the Australian Coal Mining industry, and is increasingly being quoted in related literature (Stam, *et al*., 2012).

CASE STUDY

To determine the effectiveness of UCS/Sonic correlations for *in situ* rock strength estimation, models were created using data collected from six RTCA open cut mines and two development projects. The sites are located in the Bowen Basin in Queensland and the Hunter Valley in New South Wales. The geographic spread of the sites provides a good basis for determining the robustness of these correlations in a number of different geological environments. Creation of the models for each site and their analysis were conducted in a number of successive stages. The five stages were:

1. Data collection and compilation;
2. Review of datasets;
3. Creation of site specific correlations;
4. Creation of subset correlations; and
5. Comparison of correlations.

Data collection

Data was obtained from existing repositories on the RTCA Brisbane computer network, as well as site specific networks. The two fundamental values required to create a valid sample point are the laboratory UCS test result and the average VL2F sonic velocity value over the same depth in the same borehole. Additional criteria were collected to identify potential sources of error, as well as a means of separating the full dataset into subsets for analysis of additional factors. Additional information collected included UCS test result information to identify any violations of ISRM Standards, the sample lithology, the minimum, maximum and range for each average VL2F velocity value, as well as the VL4F and VL2A velocities for comparison. Using the collected information, several values were calculated including the sample length, which is the difference between the depths of the top and base of the sample; Length-to-Height (L: H) Ratio, the ratio of the core sample length to the UCS sample height; and the Height to Diameter (H: D) Ratio.

Review of datasets

One of the major problems identified in the previous RTCA study was that underlying error in the data had not been identified and removed from the datasets (Butel, 2012). To reduce the impact of identifiable errors on the correlations, a review of the data was performed. Only sources of error in the UCS test procedure and the sonic velocity log were targeted in this review, as these were the only factors able to be adequately investigated from the data available. Importantly, during the project only samples containing identified errors were able to be removed according to the information provided. This limited the analysis significantly as only errors related specifically to the UCS test and spiking in sonic logs could be thoroughly measured. Major sources of error identified and removed from the datasets in this analysis included:

- UCS Testing;
    - Non-compliant sample dimensions;
    - Defect or bedding in sample;
    - Failure mechanism indicating problem with test – end failure, conical; and
    - Test significantly different to ISRM standards;
- Sonic Logging;

   - Cycle skipping or spikes;
   - Problems associated with the water level downhole;
   - Measurement error, including poor vertical resolution (10 cm increments);
- Other;
   - Lithology - conglomerate, pebbly, schist;
   - Outliers; and
   - Suspicious Legacy data – missing information.

Subset correlations

Subset correlations were created for each site to determine if factors other than UCS were affecting sonic velocity values, and therefore the quality of the correlations. This was performed by dividing the dataset into subsets based on the factor being analysed and creating new correlations from these. A factor was deemed to have a significant impact on the dataset if a strong correlation was able to be produced from the subset models. The factors analysed in this project included:

- Lithology (rock type);
- Overburden pressure (depth);
- Mining horizon;
- Velocity range;
- L/H ratio;
- Drilling program;
- Regional location; and
- Laboratory.

Several factors were obtained from previous research including lithology, velocity range and overburden pressure (depth) (Lawrence, 1999; McNally, 1990). Other factors were identified as potential sources of error in the data review stage.

Comparison of models

Site-wide and subset correlations were compared at each site to determine which model was the best predictor of *in situ* rock strength. The criteria for determining whether the subset models were an improvement on the site wide models included:

1. The coefficient of determination (R^2) increased;
2. The size of the subset was > 30 sample points; and
3. Strong correlations were able to be obtained for all models within a subset where there were multiples (i.e. lithology)

Site-wide and subset models were also compared across sites to determine if there were recognizable trends.

RESULTS

The figures shown are only for the site wide and subset correlations which showed significant impacts on the data spread. These factors included lithology, L/H ratio and sonic velocity range. The sonic velocities shown in all figures are VL2F although both VL4F and VL2A models were also produced. No signficant improvements in quality were identified in the VL4F and VL2A models.

Figure 4 shows the site wide correlation for HVO. The R^2 value for this correlation is 0.54, which is below the industry benchmark of 0.7. The initial dataset contained 406 samples. After the data review, 58 points were removed due to errors, leaving 348 points in the final dataset. The data shows a regular trend for this type of model with few points in the low velocity range, and becoming broadly spread in the high velocity range. The confidence interval is close to the regression line indicating the line fits the data well, although it does deviate above 4500 m/s. The data spread indicates that there is a ±30 MPa variation around the regression line in the high velocity range (>3000 m/s), and ±10 MPa in the low range (< 3000 m/s). This indicates that there is high variability in the predictive confidence of this model at high velocities.

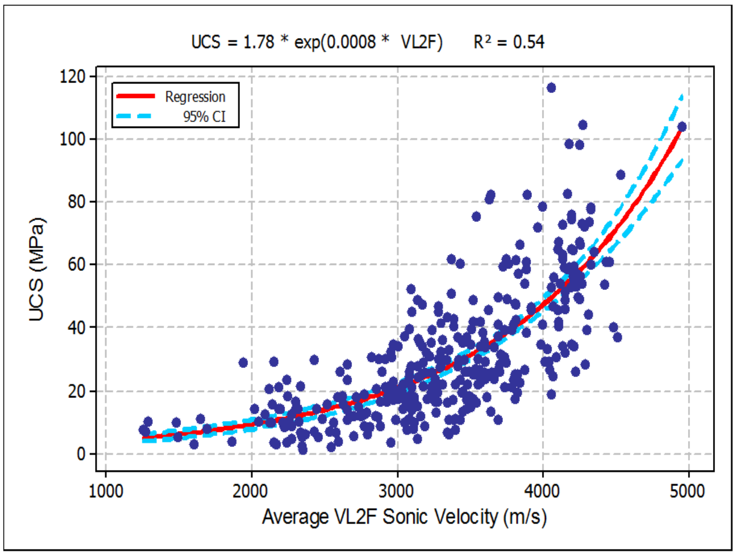

Figure 4 - HVO site wide correlation

Two correlations have been created for sample points with velocity ranges less than 100 m/s and 250 m/s (Figure 5). The correlations have very similar trend line equations and moderate R^2 values. The 100 m/s model has an R^2 of 0.64 for a dataset of 99 points. The 250 m/s model contains 203 sample points and has an R^2 of 0.62. These present a significant increase in R^2 compared to the site wide model.

The HVO dataset has been filtered by L/H ratios of less than 1.5 and 2 (Figure 6). The equations for the two models are similar to the site wide model. The L:H < 1.5 model has a fair correlation at 0.58 using a small dataset of 39 points, compared to a correlation of 0.51 using 139 points for the L:H < 2 model. The L:H<1.5 model presents a slight increase in R^2 compared to the site wide model, and the L:H<2 shows a slight decrease.

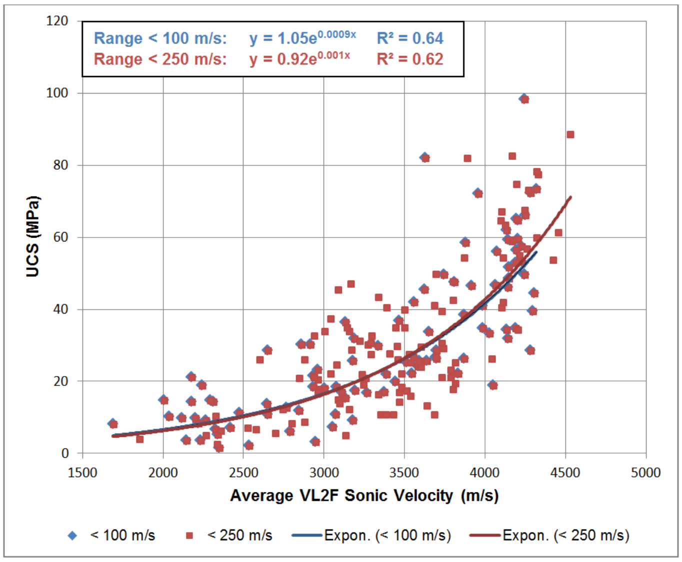

Figure 5 - HVO velocity range correlations

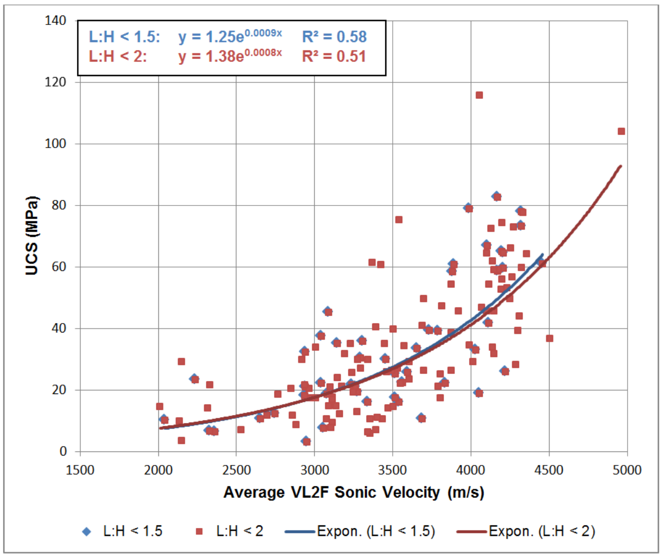

Figure 6 - HVO L:H ratio correlations

Lithology models have been produced for Interbedded Sandstone/Siltstone, Siltstone, Sandstone, and Shale (Figure 7). Sandstone displays a reasonable correlation with an R^2 of 0.59 for a dataset of 180 points. This represents an improvement compared to the site wide model. The other correlations are generally poor, with R^2 values below 0.4. The siltstone, interbedded siltstone/sandstone, and shale models contain 73, 35 and 18 sample points respectively.

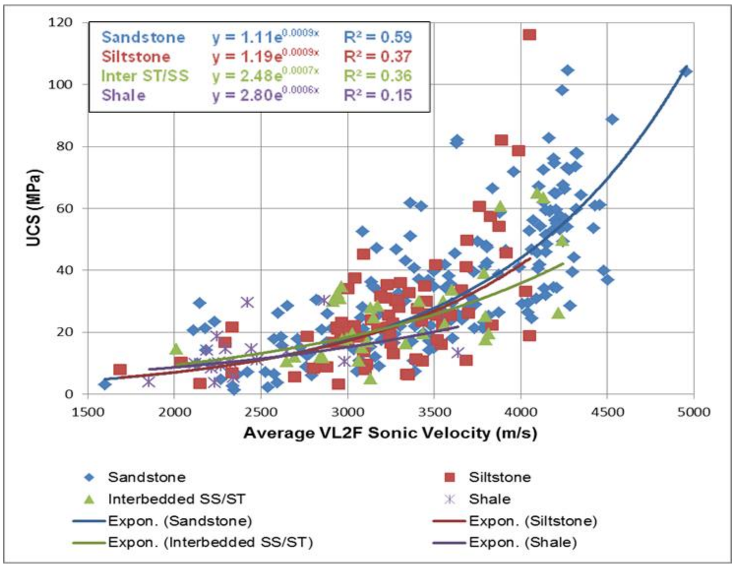

Figure 2 - HVO lithology correlations

Comparison of subset and site-wide models

Tables 2 and 3 show comparisons of R^2 values and dataset sizes between the L:H Ratio and Velocity Range models to the site-wide model for all sites reviewed in this project. In most cases there is a reasonable increase in R^2 for subset models compared to the site-wide model. However, the datasets for the L:H < 1.5 and range < 100 m/s models are generally too small to be reliable, containing less than 30 sample points.

Table 2 - Comparison of L:H and site models

Model	L:H < 1.5		L:H < 2		Site-Wide	
Site	R^2	n	R^2	n	R^2	n
BA	0.82	14	0.69	36	0.64	49
HCK	0.64	55	0.55	156	0.57	257
WIN	0.73	15	0.75	36	0.73	52
CLM	0.32	22	0.12	129	0.14	279
HVO	0.53	49	0.51	148	0.54	348
BMC/MTP	0.3	38	0.36	73	0.35	84
MTW	0.23	46	0.25	219	0.15	387

Table 3 - Comparison of range and site models

Model	< 100 m/s		< 250 m/s		Site-Wide	
Site	R^2	n	R^2	n	R^2	n
BA	0.85	8	0.69	22	0.64	49
HCK	0.46	41	0.48	146	0.57	257
WIN	0.16	7	0.67	22	0.73	52
CLM	0.02	46	0.09	147	0.14	279
HVO	0.64	99	0.62	203	0.54	348
BMC/MTP	0.23	18	0.49	51	0.35	84
MTW	0.13	49	0.17	209	0.15	387

ANALYSIS

Site wide

The overall results show that most of the site-wide models produced an R^2 value below the industry benchmark for a good correlation of 0.7. Some of the site models are of such poor quality that they cannot be used in their current form with confidence. These site models include MTW, Clermont and Bengalla. Other sites show reasonable trends although they still do not meet the 0.7 benchmark. These include HVO, Hail Creek, Blair Athol, Mt Pleasant, and BMC/MTP Combined. These models can be used for *in situ* rock strength prediction but with caution. Winchester South is the only site-wide model that exceeds an R^2 of 0.7 indicating that it is a good quality correlation. The main cause of these low values is the large spread in UCS values for sonic velocities greater than 4000 m/s. This indicates that there is a large amount of variability in UCS not being accounted for in these models.

A number of subset correlations based on potential sources of error in the data were created to determine if these are affecting the spread in the data. The results indicate that lithology, velocity range and L/H ratio have the most significant impact on the data spread. In most cases correlations with stronger R^2 values compared to the site wide models were able to be produced from the subsets. This analysis indicates that these factors are contributing to the spread in the data shown in the site wide models.

L / H ratio

One major source of potential error found during the data review was that the sample depth quoted in UCS test result sheets did not correspond to the height or position of the sample tested. The sample depths were generally much larger than the actual sample height. This was up to four times in some samples. This is because the core lengths sent to the laboratory needs to be large enough to ensure a good quality sample of sufficient height and without defects. However, the location at which the test sample is taken from along this length is not recorded. The problem is that average sonic velocity values must be taken over the entire sample depth range, which introduces a large amount of uncertainty into sample points where the ratio of sample length to sample height is high. Furthermore, it is speculated that where a large core length has been provided, this may indicate that the core was fractured or poor quality, which would also cause problems for the sonic log measurement at this depth.

To determine whether this discrepancy was having a major impact on the models, the datasets were filtered by sample points with L:Hratios of less than 1.5 and 2. For L:H less than 2, this typically resulted in a reduction in the size of the dataset by approximately 40%, and for less than 1.5 the dataset was reduced by 80%. The reduction in the dataset size for the L:H < 1.5 model generally made them unusable as there were less than 30 sample points. The improvement created by filtering the dataset using L:H can be seen in Hail Creek and for MTW, as well as for Blair Athol, Winchester South, Bengalla, Mt Pleasant, and HVO. Table 2 highlights the differences in R^2 between the site-wide model and subset models for all sites. The largest improvement was shown by MTW, with a 0.10 increase in R^2 by applying the L:H < 2 filter. This indicates that L:H ratio does have an impact on the variability in the data, and that by filtering the dataset using this factor the correlation can be improved.

Sonic velocity range

A second source of error in the correlations is large velocity ranges in sample points. These points are likely to be affected by fractures in the rock, or changes in lithology, which skew the average velocity value. These velocity values are probably not representative of the corresponding UCS sample, as UCS samples are intact rock core without bedding or changes in lithology. McNally (1990) suggested that correlations may be improved by choosing samples corresponding with flat sections on logs, and avoiding sections where the log gradient is steep. McNally's recommendation has been applied to this research and it has been found to improve the quality of correlations. Site datasets were filtered by sample points with sonic velocity ranges of less than 100 m/s and 250 m/s. These filters reduced the size of the dataset by on average 50% for 250 m/s and 80% for 100 m/s. These correlations generally produced higher R^2 values than the full dataset models (Table 3). The HVO velocity range < 250 m/s correlation showed a significant increase in R^2 to 0.62, compared to 0.54 for the site-wide model (Figure 4). The largest increase occurred in the combined Bengalla and Mt Pleasant model, which showed a 14% increase in R^2 (Table 3). This indicates that this filter can help to reduce some of the underlying variability in the data.

Lithology

Lithology correlations showed varying levels of success in explaining the spread in the data. At most sites reasonable sandstone models were able to be produced, such as Blair Athol, Winchester South, and HVO. At some sites strong siltstone and interbedded sandstone/siltstone models were also able to be produced, including Blair Athol, Winchester South and Bengalla/Mt Pleasant combined. Other lithologies were not able to be adequately modelled due to the small size of the subsets. One observation that was noted is that Clermont Mine dataset contains a significant amount of samples points with conglomerate, basalt and schist lithologies. From the Clermont dataset, a strong correlation for Basalt was able to be created with an R^2 of 0.74. However conglomerate data correlated very poorly, with an R^2 of only 0.22. The quality of lithology correlations is due to the composition of the rock. Conglomerate consists of high strength clasts (pebbles, rock or boulders) within a low strength fine grained matrix. This causes high sonic velocities as compression waves reflect off the clasts, but low UCS due to failure in the matrix. This effect was also noted in other lithologies containing a significant 'pebbly' component, such as pebbly sandstone. Other rock types which have a more consistent grain size have been shown to correlate much better. To improve the quality of correlations, sample points with conglomerate or pebbly components should be removed from the dataset.

A significant limitation of adopting lithology correlations over a site-wide correlation is the added complexity in applying these models to UCS contour mapping. Different models must be used in different zones where the geology changes, and then they must be amalgamated into a single map to be useful. This increased complexity makes the models less attractive and therefore less likely to be used in mine planning and design. Although strong correlations can be produced for some lithologies, overall these models are impractical and do not include all lithologies present on mine sites.

Legacy data

A third source of error identified in the analysis was that legacy data introduced a moderate degree of uncertainty into the datasets. For a number of sites, most of the additional information that would normally be used to identify errors was not available. This limited the ability to review the data for errors, so these sample points were treated with caution during the analysis. Attempts were made to identify irregularities by looking for significantly different trends in the drilling program and laboratory correlations. In the Hail Creek drilling program correlations, the 200 and 400 series sample points showed distinct trends from the rest of the dataset and had very little additional information available on the UCS test results. Therefore these sample points were removed from the dataset for all other correlations.

Another issue arising from the legacy data is that in some cases it has already been highly filtered. The Hail Creek Laboratory correlations show a very strong model for the Mackay laboratory, which includes legacy data from 2005. It appears that this data has already been filtered to produce the strong correlation shown by this model. Therefore this introduces bias into the dataset as the spread in the historical data is not fully represented. The unfiltered datasets for these holes were unable to be located during the data collection stage.

Measurement error

A major issue identified during the completion of this project was that where the site wide model showed a very low correlation, it was very difficult to produce significantly improved subset correlations. This was particularly evident in the Mount Thorley Warkworth models, which produced an R^2 of 0.30 in the best subset correlation. This is likely to be due to sources of error in the main dataset being unable to be filtered out in the subset correlations due to a lack of available identifying information. Based on previous research conducted in this field, these unidentified sources may include measurement error, rock density, composition, porosity, and the impact of discontinuities on sonic logs.

A key limitation of this research is that the cause of errors in sonic logs was unable to be identified from the data provided. Measurement error has been recognized at several sites which may have contributed to the poor quality of correlations (Guy and Bamberry, 2011; Turner, 2009). In the MTW dataset, a large number of the removed sample points had problems with the sonic velocity value caused by cycle skipping or spikes in the log. Two holes in particular contained a large number of issues in the sonic log. Although this cannot be confirmed based on the information available, it is suspected that these problems are associated with measurement error. Implementation of a standardised sonic velocity logging manual is expected to reduce the amount of measurement error present in samples in the future.

Standardised sonic logging procedure document

Currently there is no standardised procedure for sonic velocity logging across all RTCA sites. Furthermore, no comprehensive and informative international or Australian standards exist for sonic velocity logging. The quality and reliability of these models depends on the accuracy of sonic velocity data collected from site. This has been raised as a major potential source of measurement error, as different logging companies or individual loggers may use different standards (Guy and Bamberry, 2011). Another problem is that it is very difficult to identify this error in the sonic logs. To address this problem at RTCA sites, a draft version of a standardised sonic logging procedure was created as part of this project. This document is to be reviewed and potentially implemented at all RTCA sites in the future. The purpose of this document is to ensure adequate calibration, measurement, quality control, and data presentation is achieved for all sonic logs, so that the best possible quality data can be collected.

CONCLUSIONS

The aim of this project was to create improved UCS/Sonic correlations that can be used with confidence for mine planning and design. Analysis of the correlations created for RTCA sites has shown that improved models can be obtained by filtering the datasets to remove samples with high L/H ratios and large sonic velocity ranges. There is some evidence indicating that lithology specific models could produce stronger correlations than site-wide models. However, it was concluded that these models should not be used in replacement of the site-wide models because of the increased complexity required to create UCS contour maps based on these models. Sample points containing conglomerate and pebbly components should be removed from datasets to improve the quality of correlations. Similarly, mining horizon, depth, localised, lease, and lab models did not show significant improvements compared to the site-wide model. Therefore the site-wide correlation filtered by length-to-height ratio and sonic velocity range is considered to be the most appropriate model for the purpose of *in situ* rock strength prediction for this dataset. If good quality data already exists for a site, UCS/sonic correlations can be used as effective predictors of *in situ* rock strength with confidence at virtually no cost. Sonic derived UCS contour maps can be easily created from these models, which can be used in a number of important mine planning and design applications such as:

- High/low wall slope stability analysis;
- Open cut blast design optimization;

- Underground principal hazard management plans;
- Underground roof support design; and
- Drill performance optimization.

The overall quality of the models shown in this analysis has been significantly below the industry benchmark for a good correlation. The main reason for this is that a component of the variability in UCS has not been accounted for in the model. A source of this variability is believed to be measurement error from sonic velocity logging, which was difficult to identify and remove with the information available. This problem was particularly noticeable at NSW sites including MTW, HVO and BMC. This has previously been identified as a major issue in the sonic logs at these sites (Guy and Bamberry, 2011; Turner, 2009). A draft standardised procedure for sonic velocity logging has been developed to reduce measurement error in data collected in the future. Other factors not accounted for in UCS/Sonic models are also contributing to the large spread in the data plots and low correlation quality. Research suggests these factors include rock density, porosity, composition, shale content and discontinuities.

RECOMMENDATIONS

To improve the quality of UCS and sonic velocity correlations, six key recommendations have been made based on this research. These include:

1. Record the exact depth of UCS samples after cutting at the lab to reduce error associated with L/H ratio;
2. Remove sample points with large velocity ranges affected by changes in lithology or discontinuities;
3. Identify and remove suspicious legacy data skewing the data trend;
4. Utilise a standardised sonic velocity logging procedure proposed as part of this research to reduce the amount of measurement error, and ensuring it is consistent across all samples;
5. Develop Australian standards for geophysical logging to allow accurate UCS prediction to be undertaken, and for better comparison of data between sites; and
6. Perform laboratory sonic velocity logging as a form of quality control by comparing lab and field results.

This is expected to significantly reduce the amount of error currently present in the models, and improve confidence in applying these models to mine planning and design.

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