The Extended Mathews Stability Graph: Quantifying case history requirements and site-specific effects

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Abstract and Resume

Narrow vein underground stope design engineers in Australia have expressed significant interest in the requirements and methodology for developing site-specific stability charts. This is largely due to a concern that existing stope stability charts inadequately take into account factors influencing narrow vein stope stability, such as the effect of backfill abutments and the effect of in stope pillars. This paper presents conclusions from a comprehensive statistical examination of case history requirements for a site-specific stability chart and critiques literature arguments for site-specific charts. A new statistical analysis technique and a large comprehensive stability database enabled the authors to quantify case history requirements and any site-specific effects the model exhibits.

The analyses indicated that a reliable stable-failure boundary requires at least 150 case histories, of which a minimum of 10 percent should be unstable stope surfaces. Marginal site-specific effects were observed for the operating conditions captured within the database. The authors conclude that the apparent site-specific effects noted in previous literature are attributable to operating conditions inadequately represented in the database. Such operating conditions could induce erroneous stability predictions at any site, and are therefore not truly site-specific.

Following from these conclusions, a strategy for taking into account operating conditions particularly relevant to narrow vein mining has been proposed. In particular, the development of a chart that accounts for the effect of backfill abutments on stope stability. Backfill abutment effects are particularly relevant to mechanised narrow vein mining methods such as modified Avoca. Collaboration from at least five sites is required to obtain access to relevant data and underground drives for geotechnical mapping. Preliminary estimations indicate that approximately three months fieldwork is required to meet case history requirements. CMS data in conjunction with 3-dimensional design software will be used to calculate equivalent linear overbreak/slough (ELOS). In contrast to stable, failure, major failure and caving categorical variables, ELOS is an objective and continuous stability variable and is therefore, more conducive to mathematical modelling.

Introduction

The Mathews Stability Graph method is an empirical stope design tool used extensively in Australia and Canada. Over the last few years a much larger database of case histories from a wide variety of geotechnical environments has been developed for the technique (see Trueman et al, 2000; and Mawdesley et al, 2001). Trueman and Mawdesley (paper awaiting permission to publish from sponsoring companies) have also extended the technique into the prediction of caveability. The current database comprises 486 case histories of stope surface stability of which 317 were stable, 154 had experienced failures or major failures and 15 continuously caved. This data was collected from 35 mines from Australia, Canada, Chile, the United Kingdom, the United States and Zimbabwe. A wide variety of geotechnical environments and stope surface geometries are included in this database, with Q' values ranging from 0.01 to 90, while hydraulic radii range from 1 to 55. Logistic regression was used to determine stability boundaries (Mawdesley et al, 2001). The original method of determining the
stability number developed by Mathews et al (1981) is adhered to in this extended version of the Mathews method, rather than the modified version developed by Potvin (1988); see Trueman et al (2000) and Mawdesley et al (2001) for a discussion on this. This particular variant of the Mathews method has been termed the Extended Mathews Stability Graph.

Some concern has been expressed by a number of authors about the general applicability of the Mathews method. Mathews et al (1981) and Potvin (1988) noted that the method was originally developed for open stope mining methods in geological conditions similar to those encountered in the Canadian shield. Stewart and Forsyth (1995) whilst acknowledging that there are some indications that the method may be generally applied, emphasised the potential bias in their much more limited database and recommended users concentrate on collecting sufficient examples to define their own stability zones. Bawden (1993) also suggested that the analysis of stable versus failed stopes can be used to derive a stability boundary for a particular operation. From their experience of back-analysing a large data base from the Mount Charlotte gold mine in Western Australia, Trueman et al (2000) concluded that the model gave reasonable predictions of stope surface stability, at least for steeply dipping deposits in moderately good to good rock. Nevertheless, Trueman et al followed the guidelines of Stewart and Forsyth and developed a site-specific chart for Mount Charlotte. There is currently significant interest being shown in the development of site specific Mathews Stability Graphs within the Australian metalliferous mining industry in general and particularly for narrow vein deposits.

The original Mathews Stability Graph for open stope design (Mathews et al, 1981) had only 50 case histories. The collection of more data by Potvin et al (1988), Stewart and Forsyth (1995) and Trueman et al (2000) increased the case history data that resulted in changes to the stability boundaries. Trueman et al (2000) from their experience at the Mount Charlotte mine estimated that at least 100 case histories would be needed to determine a reliable site specific Stability Graph. However, this estimate was not arrived at from a rigorous analysis. An indication of how many case histories would be required to determine reliable stability boundaries is a pre-requisite for the development of a site specific variant. Additionally, because of the paucity of reliable continuous caving case history data Trueman and Mawdesley (paper awaiting permission to publish from sponsoring companies) considered this very important in judging the reliability of their all failure-continuous caving boundary.

The qualitative nature of the stability category has meant that, until now, the relative reliability of a site-specific line to the ‘generic’ line, involved comparing the number of misclassified points until the design engineer was confident the site-specific line was more reliable than the generic stability line. In cases where site-specific effects appear to be affecting the reliability of the generic stable-failure boundary, this approach seems reasonable. However, inherent in this approach is the assumption that the site-specific database is sufficiently large to justify changing the stable-failure boundary. If the database is inadequate, the design engineer may make changes to the stable-failure boundary attributable to short-term operational conditions rather than any real site-specific factor.

This paper sets out to answer the question of how many case histories are required to set a reliable stability boundary, what proportion must be of a different stability classification and how site specific is the Extended Mathews Method. Use is made of a logistical regression technique to quantify these. Until now, there has been no way of rigorously determining database requirements for a stable-failure boundary. This question has been answered by analysing variance in model parameters. Once the database requirements were quantified in terms of number and type of points, the authors could statistically examine whether site-specific model parameters are significantly different from the generic database.

Site-specific effects

There is substantial anecdotal evidence that site-specific effects may result in erroneous stability predictions. Greer (1989) back analysed Thompson mine data to determine how well Potvin’s modified stability chart predicted stability at this particular site. Greer’s analysis (Bawden, 1993) found unstable hangingwall points were largely misclassified as stable. Although this particular case uses Potvin’s modified stability graph, the Extended Mathews Stability Graph would have predicted similarly erroneous stability predictions. Greer identified operational conditions such as blast damage, the effect of adjacent sand fill and delays to filling as likely causes for the misclassification. Early versions of the vertical crater retreat method were used during this period of the Thompson mine life. This method can
result in significant blast damage due to inherently more blasting confinement and higher powder factors than long-hole stoping. Additional examples of inaccurate stability prediction are the Winston Lake hangingwalls (Milne, 1997). The assumption sandfill provides the same abutment characteristics as solid rock could be a source of erroneous stability prediction for the Winston Lake mine. Milne concluded, from comprehensive hangingwall monitoring at the Winston Lake mine, that treating backfill limits the same as rock abutments is overly optimistic. The Thompson and Winston Lake mines are both examples of sites where apparent site-specific effects may have impacted adversely upon the ability of a generic stability graph to predict stability. However, it could be argued that these effects are not truly site-specific. The authors of this paper propose that similar operational conditions would have resulted in erroneous predictions at any mine site and are therefore not truly site-specific.

In this paper, the authors present the findings of a case study into the statistical significance of site-specific effects. The site to be investigated is the Mt Charlotte mine in the eastern goldfields of Western Australia. Site visits to Mt Charlotte present no obvious site-specific parameters (Trueman et al. 2000). Logit model parameters and comparative statistics have been used to determine whether there is a significant difference between the Mt Charlotte stable-failure boundary and the generic stable-failure boundary developed for the Extended Mathews Stability Graph. There are no apparent operational conditions to explain why the site-specific line would be significantly different to the generic stable-failure line. Therefore, if there were a significant difference, it would be evidence of the existence of site-specific effects. Ideally the authors would prefer to have investigated the same hypothesis with respect to other sites. However, Mt Charlotte is the only site that meets database requirements.

The Extended Mathews Stability Graph

The Mathews stability chart method was originally developed in 1980 as part of a CANMET report into stope stability in deep Canadian mines (Mathews 1981). Since then, a number of authors have added data (Potvin 1988; Trueman et al 2000), proposed modifications to the way the stability number is calculated (Potvin 1988; Sprott et al 1999; Diederichs and Kaiser 1999; Kaiser et al, 2001) and recommended changes to the way stability categories are represented on the chart (Hadjigeorgiou et al 1995; Stewart and Forsyth 1995; Mawdesley 2000). However, due to the absence of data in the fields required to incorporate these modifications, it has not been possible to apply nor test the validity of these modifications with respect to the Extended Mathews Stability Graph database. For this reason, the authors have retained the original Mathews stability chart method (Mathews 1981). For consistency, the authors have adopted the standard approach to calculating N and S recommended by Stewart and Forsyth (1995). N and S are calculated according to equation 1 and equation 2; where N is the stability number, A is the rock stress factor, B is the joint orientation adjustment factor and C is the gravity adjustment factor. Q' is the NGI Q classification index value (Barton, 1974), with the SRF and joint water reduction factors set to 1.

\[ N = Q' \times A \times B \times C \quad \text{Equation 1} \]

\[ S = \frac{\text{Surface Area}}{\text{Surface Perimeter}} \quad \text{Equation 2} \]

The stable-failure boundaries discussed in this paper were determined using logistic regression. The advantages of delineating the stable failure boundary mathematically, as opposed to by eye, include; increased objectivity and the ability to quantify variance in the stable-failure boundary. The ability to measure variance in the stable-failure boundary model parameters has facilitated the authors in their analyses. The logistic regression line defining the stable-failure boundary is defined by equation 3 and equation 4 (DeMaris 1992; Mawdesley et al 2001), where P(z) is the logit value. The logit value is analogous to the response variable in a linear regression model and is determined for each data point based upon the stability number N, the hydraulic radius S and the stability. Stability is the categorical response variable and is assigned a value. In ordinary binomial logit models, the categorical response variable would be assigned a value of 1 or 0. However, in the case of the stability graph, there are four categorical response variables; stable, failure, major failure and caving (Mawdesley, PhD in preparation University of Queensland). In order to incorporate these four response levels, the following
values were assigned; stable points were set to 1, failures were set to 0.6 while major failures and caving points were set to 0.3 and 0, respectively as noted by Mawdesley. The logit values are calculated using a MATLAB routine developed by Holtsberg (1998).

\[ z = \beta_1 \ln(N) + \beta_2 \ln(S) + \beta_3 \]  
Equation 3

\[ P(z) = \frac{1}{1 + e^{-z}} \]  
Equation 4

To evaluate the stable-failure logistic regression line; \( P(z) \) is set to the logit value at the intersection of the cumulative probability function for stable points and the inverse cumulative probability function for failures. This represents the logit value that separates stable points and failures with the least amount of error. Using equation 4, it is then possible to evaluate the prediction, \( z \) and substitute this value into equation 1 to determine the stable-failure logistic regression line. The logit model parameters \( \beta_1 \), \( \beta_2 \) and \( \beta_3 \) are determined using the maximum likelihood function contained within the Matlab procedure logitfit (Holtsberg 1998).

In the case of the generic stable-failure logistic regression line developed for the Extended Matthews Stability Graph; 81 percent of stable points correctly reported to the stable zone, while 84 percent of the unstable points correctly report below the stable-failure boundary. The extended Mathews Stability Graph is best thought of as a three-dimensional probability surface, where the probability of a case history being stable, or unstable, is defined by its position in the two-dimensional graph space. Figure 1 is the extended Mathews stability graph (Mawdesley, PhD in preparation). It is possible to evaluate the probability of stability or failure at any point on the graph.

![Figure 1 – The extended Mathews stability graph (after Mawdesley, PhD in preparation University of Queensland)](image)

Analytical Technique

Previous Limitations

The logit model predicts a three dimensional surface of probabilities, not a two-dimensional boundary. In the case of logistic regression there is no agreed upon technique to quantify the quality of the logistic
regression line (Whiten personal communication, 2001). Logistic regression does not have a technique equivalent to the analysis of variance approach that would be used for a least squares regression model (Devore, 1991). For this reason, the authors have developed a new approach that analyses the effect of changing database parameters, such as the number of case histories, on model parameter variance.

The MATLAB procedure logitfit (Holtsberg, 1998) evaluates confidence intervals for model parameters $B_1$, $B_2$ and $B_3$. However, logitfit does not provide confidence intervals for the logit models defined by equation 2. The authors attempted to produce confidence intervals for the stable-failure logit boundary using the Monte Carlo simulation function in the @Risk program (Palisade, 1996). The Monte Carlo simulation uses random combinations from the probability distributions of each model parameter to produce a stochastic model. The results of the Monte Carlo simulation produced impossibly large stability numbers. The impossibly large stability numbers produced by the model indicates the existence of mathematical dependencies between $B_1$, $B_2$ and $B_3$. Extensive plotting of model parameters indicates model parameters are mutually dependent. The authors concluded that due to dependencies between the model parameters, $B_1$, $B_2$ and $B_3$, a Monte Carlo simulation could not be used to determine confidence limits for the stable-failure boundary.

Quantifying logit model reliability

Defining the relationships between the model parameters was beyond the scope of the research project. Therefore, an alternative analytical technique was required. For this reason, the authors developed an analysis technique to facilitate a parametric study of the effect of database parameters on logit model reliability. The technique analyses the variance of logit model parameters, $B_1$, $B_2$ and $B_3$ for different database scenarios. Ten random samples were taken from the generic database to represent each database scenario. The mean and standard deviation was calculated for each set of ten random samples. Trends in the variance were analysed using normalised standard deviation. Standard deviation has the same units as the mean, and is therefore normalised by division by the mean. By definition, minimising the variance in model parameters means further increases to the size of the database will not improve the reliability of the stable-failure boundary. When the gradient of normalised standard deviations of $B_1$, $B_2$ and $B_3$ level out, there are no further gains to be made by increasing the size of the database. This analytical technique provides a method for comparing the reliability of various database scenarios.

Assumptions

The technique assumes the generic database, from which random samples were taken, is sufficiently large to not invoke trends in the variance. For example, if the database had been comprised of only 250 points and ten sets of 200 samples were taken, one would expect the variance to be smaller than if ten sets of 100 random samples were taken. This assumption was tested. The results obtained were consistent with the hypothesis that the variability in $B_1$, $B_2$ and $B_3$ will decrease at a greatly reduced rate once the database size reached a critical size. The much smaller ongoing decreases in variability with increasing sample size can be attributed to sample size approaching that of the database. This indicates the generic database was sufficiently large to observe the hypothesised relationships between model parameter variance and database sample scenario. If the database had been too small, the levelling out of the normalised standard deviation would not have been apparent and the technique would not have enabled any clear results to be obtained.

A second assumption of the technique is that the generic 486 case history database developed for the Extended Mathews Stability Graph is a representative sample of the population of all stope surfaces from which data could, theoretically, have been collected. The generic database comprises of data from 35 mines, including the broad range of open stoping variations used in Australia, Canada and the United Kingdom and from a broad range of geotechnical environments and stope dimensions. However, it is not possible to quantify, in absolute terms, whether the generic database represents the total stope surface population. Nevertheless, the range of data and variety of sources of data contained in the generic database ensures that it is a reasonable representation.

The logistic regression line variance is also affected by the value of $p$, as defined in equations 3 and 4. As the value of $p$ is not independent of $B_1$, $B_2$ and $B_3$, it was necessary to check the magnitude of $p$ value variance. The variance of $p$ was found to be less than 5 percent over all database scenarios.
Therefore, it was possible to analyse the variance in $B$ with respect to database size independently of $p$. The variance in $p$ would be very small provided there is an even distribution of data. In particular, that there are sufficient points close to the stable-failure boundary.

Results

Parametric study of database requirements

Two database requirements were examined; the number of case histories in the database and the proportion of unstable points in the database. Figure 2a, 2b and 2c illustrate trends in the normalised standard deviation for $B_1$, $B_2$ and $B_3$, respectively. There is a clear change in gradient as random sample size levels out rapidly when random sample size is approximately 150 case histories. Thus, analysis of variance in logit model parameters indicates approximately 150 case histories are required to minimise variance in model parameters. The ongoing small decrease in parameter variance beyond 150 case histories can be attributed to the sample size approaching the size of the database, such that the normalised standard deviation reaches zero when the sample is the database.

![Figure 2a – Effect of sample size on normalised standard deviation of $\beta_1$](image)
A similar analysis examined the effect of the proportion of unstable case histories as a percentage of the total number, on model parameter variance. Each case history in Figure 3 represents statistics for the logistic regression results of ten random samples of 200 case histories. Trends in the normalised standard deviation indicate that between 10 and 12 percent unstable case histories are required to minimise variance in model parameters. Minimised normalised standard deviations range between 7 and 10 percent for each of the model parameters. In this case, the normalised standard deviation approaches a semi-asymptote. Parameter normalised standard deviations fluctuate about this semi-asymptote due the interdependence of model parameters.
An important observation was made when plotting variously sized random database logistic regression lines. It was found that the variance in the model parameters $B_1$, $B_2$ and $B_3$ has greatest effect for regions of the chart beyond the range of the data. Based upon this observation, the authors recommend stable-failure boundaries should not be extended beyond the range of the data. In addition, as shown in Figure 1 the stable failure boundary is characterised by excellent data coverage. The authors believe that an additional database requirement is data coverage. For this reason the authors believe that the reliability will most likely depend upon data coverage. Further investigations are required to determine the effect of regions of absent or very limited data.

Preliminary investigations indicate the conclusions regarding data base requirements can be extrapolated to the failure-continuous caving boundary previously noted. However, further analysis is required to confirm these findings. At this time, the failure-continuous caving boundary can not be published due to intellectual property restrictions on this work.

Mt Charlotte – Case study

The generic Extended Mathews Stability Graph (Trueman et al 2000; Mawdesley et al, 2001) gives reasonable predictiveness for site specific data, although not quite as reliable as a site-specific logistic regression line. Table 1 compares the reliability of the site-specific stable-failure boundary to the reliability of two variations of the generic stable-failure boundary. The generic boundary including Mt Charlotte is the logistic regression boundary for the entire 486 case history database, while the generic boundary excluding Mt Charlotte is the result of logistic regression of the remaining 272 case histories. Mt Charlotte was excluded from the database to remove potential bias in the generic database. Sensitivity is defined as the percentage of stable points that report correctly to the stable zone, while specificity is defined as the number of case histories that report correctly to the unstable zone. The site-specific boundary resulted in a 3.7 percent increase in the sensitivity and a 3.9 percent increase in the specificity compared to the generic boundary including Mt Charlotte. In the case of the generic boundary excluding Mt Charlotte data, the increase in sensitivity was 8.0 percent and the increase in specificity was 8.6 percent.
TABLE 1 – Effect of site specific boundary on specificity and sensitivity

<table>
<thead>
<tr>
<th></th>
<th>Mt Charlotte Boundary</th>
<th>Generic Boundary - Including Mt Charlotte data</th>
<th>Generic Boundary - Excluding Mt Charlotte data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>83.3%</td>
<td>79.6%</td>
<td>75.3%</td>
</tr>
<tr>
<td>(Percentage of Mount Charlotte stable case histories correctly reporting to stable zone)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>73.1%</td>
<td>69.2%</td>
<td>64.5%</td>
</tr>
<tr>
<td>(Percentage of Mount Charlotte unstable case histories correctly reporting to unstable zone)</td>
<td></td>
<td></td>
<td></td>
</tr>
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</table>

Figure 4 illustrates that there is a small difference between the two generic regression lines. Comparative statistics analysis was utilised to determine if this difference is statistically significant. In the case of Mt Charlotte model, comparative statistics indicated, with 95% confidence, no significant difference between Mt Charlotte, $B_1$ and $B_3$ values and the generic case, $B_1$ and $B_3$ values. However, there is a 98 percent probability Mt Charlotte model parameter $B_2$ is significantly different from the generic logit model parameter $B_2$. Table 2 summarises the results of the comparative statistical analysis. Due to the significant difference detected for parameter $B_2$, the authors decided to investigate further. The authors investigated whether this level of significant difference could be obtained between a sample and the source database. If so, then this would be evidence that the $B_2$ 98 percent significance test result could have been a type I error. A type I error occurs when the difference appears to be significant when it is not (Walpole and Myers, 1990). Table 2 contains the results of three comparative statistical analyses for three random samples of 150 from the generic database excluding Mt Charlotte data. These results show that at the 90 percent level of confidence, there are three type I errors out of the nine comparisons conducted. We know they are Type I errors because the samples come from the database and there should be no significant difference.

TABLE 2 – Comparative statistics

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Probability Mt Charlotte database is significantly different to Generic excluding Mt Charlotte</th>
<th>Probability sample of 150 cases from generic database excluding Mt Charlotte is significantly different to generic database excluding Mt Charlotte</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sample 1</td>
<td>Sample 2</td>
</tr>
<tr>
<td>$B_1$</td>
<td>79%</td>
<td>93%</td>
</tr>
<tr>
<td>$B_2$</td>
<td>98%</td>
<td>55%</td>
</tr>
<tr>
<td>$B_3$</td>
<td>72%</td>
<td>91%</td>
</tr>
</tbody>
</table>
Based upon these results the authors concluded that the 98 percent result for B₂ was a type I error and therefore, does not indicate a significant difference between Mt Charlotte and the generic database.

Mine B– Case study

The aim of this case study is to illustrate the effect of an inadequate database on the stable-failure boundary. Mine B is a real mine with 85 case histories, of which only 8 percent are unstable. Mine B currently has insufficient data to meet the database requirements. The total number of case histories is insufficient, as is the proportion of unstable case histories. The site-specific logistic regression model for mine B data did not improve the misclassification compared to the generic stable-failure boundary. In fact, the site-specific boundary produced one more misclassification than the generic stable-failure boundary. Figure 5 compares mine B site-specific stability boundary to the generic boundary. If the database requirements had been met, there may have been an improvement in the reliability of the site-specific stable-failure boundary. However, with an inadequate database it is impossible to make any conclusions about the site-specific effects at this site. However, the site-specific stability boundary does appear to predict that unrealistically high rock mass strengths are required for larger stope dimensions.
Development of an operating condition specific stability charts - Backfill Stability Chart

Apparent site specific effects have been attributed to specific operating conditions. Based upon these findings and the practical difficulty of collecting 150 case histories for a site-specific chart, a strategy for developing operating condition specific charts has been developed. In particular, the development of a chart that accounts for the effect of backfill abutments on stope stability. Backfill abutment effects are particularly relevant to mechanised narrow vein mining methods. Backfill abutments are associated with mechanised narrow vein mining methods, including; modified Avoca, top-down blasthole stoping, bottom-up blasthole stoping and cut and fill. Following from these conclusions, it is proposed that sites employing mining methods with backfill abutments merge data to produce a backfill stability chart capable of empirically capturing backfill abutment effects. The aim of this project is to facilitate the process of data collection, collation, analysis and modelling to produce such a chart.

Strategy

While retaining the same framework as the Extended Mathews Stability Graph, backfill configuration parameters will be tested for significance to stope stability. Logistic regression will be used to evaluate the relative significance of potential new parameters. Potential backfill configuration factors include; number of backfill abutments, ratio of backfilled span to total span, stope width and backfill deformation characteristics. Non-linear numerical modelling using Map3d-NL will be used to semi-numerically estimate a backfill configuration factor. Analogous to the use of induced stress as a basis for Factor A in the Mathews method, non-linear numerical modelling results are expected provide a basis for estimating a backfill configuration factor.

Collaboration from at least five sites is required to obtain access to relevant data and underground drives for geotechnical mapping. The range of rock mass conditions captured in the database will have a significant effect on the general applicability of the backfill stability chart. Preliminary estimations indicate that approximately three months fieldwork is required to meet case history requirements.
Where possible, cavity monitoring survey (CMS) data will be collected. The use of cavity monitoring surveys, CMS (Miller, Potvin et al., 1992) presents a practical method for collecting data for the continuous stope stability variable, Equivalent Linear Overbreak/Slough, ELOS, (Clark and Pakalnis, 1997). Clark and Pakalnis (1997) define ELOS as the equivalent linear overbreak along a stope height. Figure 6 illustrates the concept of equivalent linear overbreak. Using 3-dimensional design software, CMS data will be used to evaluate equivalent linear overbreak/slough (ELOS). In contrast to the stable, failure, major failure, caving categories, ELOS is an objective measurement. Dilution is dependent upon stope width, and is therefore, more subjective than ELOS. In addition, ELOS as a continuous variable, and as such, is more conducive to mathematical modelling. Evaluation of ELOS from CMS results will facilitate the development of a more objective stope stability model.

![Figure 6 – Definition of Equivalent Linear Overbreak/Slough ELOS (after Suorineni et al, 2001)](image)

Suorineni et al, 2001 defines stability categories as follows; ELOS less than 0.5 metres has been defined as stable, ELOS between 0.5 metres and 5 metres as a failure, ELOS greater than 5 metres as a major failure. ELOS is evaluated from CMS results analysed in a three dimensional design package such as Datamine-Guide or Vulcan-Envisage. The ELOS can be determined by evaluating the difference in stope design volume and actual volume and then dividing by the stope surface area. However, it is unlikely that every site will have a CMS.

Model validation will be conducted using a site not represented in the database. In addition to the aforementioned 150 case histories required for stability chart development, an additional set of data will be required for model validation.

**Conclusions**

A new technique that analyses trends in the variances of three logit model parameters has enabled the authors to define database requirements that minimise the variance in the Mathews Stability Graph method stable-failure boundary. The existence of a large and comprehensive stability database was a prerequisite for these analyses.

The parametric study into the database requirements indicates 150 case histories, of which at least 10 percent must be unstable, are required to minimise the variance in a stable-failure boundary. These requirements can be used as a guide for developing site-specific stable-failure boundaries and as a check that sufficient case histories have been collected for a generic model. These requirements apply only within the range of the current database. Preliminary investigations indicate these conclusions can be extrapolated to the failure-continuous caving boundary that has been developed for the model but which cannot be published at this stage due to IP issues.

The Mt Charlotte case study suggests that the Extended Mathews Stability Graph method predictive capability may be slightly improved by using a site-specific graph that meets the database requirements. However despite the small improvement in predictive capability noted for a Mount Charlotte site-specific variant, comparative statistics indicated no significant difference between the Mt Charlotte and generic logit models. Therefore, the Mt Charlotte case study indicates that site specific
effects may be insignificant. Further case studies are required to confirm this conclusion. Currently, despite the large database that now exists no other single mine has a sufficiently large enough database for such an analysis to be made. The Mine B case study illustrated the importance of meeting the data base requirements (minimum number of case histories and stope failures) before a reliable stable-failure boundary can be delineated.

**Recommendations**

It is possible that a site specific Mathews Stability Graph variant may give a slightly better predictive capability for that particular mine, even though the model does not appear to exhibit a significant site specific effect. However, a site-specific database should have at least 150 case histories of which between at least 10 and 12 percent must be unstable points. A site-specific boundary can not be determined with confidence until these requirements are met. Furthermore, based on observation of high variability in the stable-failure boundary beyond the limits of the data, the authors recommend the generic stable failure boundary should not be extended beyond the limits of the data. The design engineer can expect a greater reliability from the generic stable-failure boundary than a site-specific boundary that has been delineated with insufficient case histories or where the boundary is extrapolated beyond the limits of the data.

When operating conditions are significantly different from those captured in the current generic database, an operating condition specific stability charts provides a practical method for capturing the effect of these differences. For example, the effect of backfill abutments on stope stability has resulted in erroneous stability predictions. The backfill abutment stability chart project aims to develop a stability chart based upon data from a number narrow vein mining operations.

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