Towards the Implementation of Discrete Fracture Network Modelling as a Geotechnical Design Tool – Case Study of Callie Underground Mine

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ABSTRACT

Advances in technology now allow geotechnical practitioners to better describe the properties and variability of a rock mass through advances in surface and underground mapping, borehole technology and geophysical imaging. Yet the way in which practitioners use this data is not being realised to its full potential and the quality and quantity of data that is collected is often superior to the conventional design approaches that are typically adopted. A discrete fracture network (DFN) approach provides the ideal basis for using this data to generate geologically-realistic rock mass models based on parameters derived from field data, which more effectively capture the variability and rock mass behaviour. However, until recently, the DFN approach has mainly been applied to cave mining and small-scale models associated with synthetic rock mass modelling or groundwater flow modelling for the nuclear waste and oil and gas industries.

Ground support design for blocky rock masses in Australia is often dealt with in a rather traditional manner, adopting either an observational empirical approach through rock mass classification systems or conventional wedge stability analysis techniques. Using these methods requires several generalised assumptions about the rock mass fabric and excavation geometry. As such, the support system is often designed for a worst-case scenario based on a predetermined risk tolerance that the mine is willing to accept and a design block size that is generally determined by the proposed excavation dimension.

A study by Doumis (2014) used conventional wedge stability analysis and the probabilistic key block analysis software JBlock (Esterhuizen, 1996) to estimate potential block sizes and support requirements. A DFN approach has also been adopted at Callie underground mine using FracMan[™] software (Golder Associates, 2014). The methodology of the DFN wedge analysis will be compared with the key block analysis work undertaken by Doumis.

INTRODUCTION

The Callie Underground gold mine (CUG) is located 531 km north-west of Alice Springs in the Northern Territory. The underground mine has been in production since 1998, and has a current production rate of 1.85 Mt/a, producing approximately 325 000 oz of gold. The mining method currently employed at CUG involves longhole open stoping with backfill. Historically, backfill primarily consisted of cemented aggregate fill via holes drilled from the surface and loose rock fill, with current practice incorporating rock fill and pastefill to fill all stoping voids.

Rock mass conditions at CUG are good quality, with low stress in the upper levels of the mine (to a depth of 800 m below surface) and signs of moderate stress in the deeper levels (1100–1650 m). Rock mass failures are rare in development,

and the observed failure mechanisms are mainly structurally controlled gravity falls resulting from changes in many factors, including blast damage, blasting vibrations and stress conditions.

This paper presents a case study of a recent ground support design project undertaken at Newmont Mining Corporation's Tanami operation in the Northern Territory, Australia. The first component of the project was a structural analysis of the rock mass conditions undertaken by Doumis (2014). The second component of the project was a ground support design assessment for CUG. At the time of writing, the ground support design assessment is ongoing, but this paper will discuss the process being followed and provide results where possible. This study used conventional wedge stability

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analysis and the probabilistic key block analysis software JBlock (Esterhuizen, 1996) to estimate potential block sizes and support requirements.

A discrete fracture network (DFN) approach has also been adopted at CUG using FracMan[®] software (Golder Associates, 2014). The methodology of the DFN wedge analysis will be compared with the key block analysis work undertaken by Doumis (yet to be completed), and the process to be undertaken will be discussed in this paper. The premise of the DFN wedge approach does not allow assumptions or limitations on the fracture system or its block forming potential. For this reason, the DFN approach is considered a true probabilistic method as it identifies blocks that are geometrically possible whilst also determining the likelihood of their formation from multiple realisations.

Through further modelling, it is anticipated that the DFN approach will provide the opportunity to optimise the ground support requirements at CUG based on a realistic 3D assessment of the fracture geometries. It also provides the ability to determine the likelihood of intersecting potentially unstable blocks in all development profiles and orientations, including intersections and stope brows.

GEOLOGY

The main orebodies at CUG are vein-hosted deposits within a complexly folded and faulted metapelite sequence. The Proterozoic sedimentary sequence has been metamorphosed to lower amphibolite facies and is carbonaceous, except where it has been altered by mineralising events. Several phases of folding and faulting have affected the Callie area, and the fold axis is oriented east-west (Basson, 2009).

The lithologies consist of various sediments, and a simplified stratigraphic column is shown in Figure 1. While the figure represents near perfect examples of well-defined lithology units, in practice, the units are difficult to distinguish. Mineralisation is typically between the Upper Blake Beds (UBB) and the Lower Blake Beds and is best developed in the Callie Laminated Beds and Magpie Schist (Basson, 2009).

The UBB is a continuous thick lithology, typically extending for more than 200 m above the orebodies. The units below the UBB contact are typically around 10 m thick. Rock mass conditions above and below the UBB contact are thus different. They are typically massive in the UBB with few joint sets, and more folded and jointed below the contact. A high degree of folding also affects the rock mass in areas proximal to the fold axis (Figure 2) (Basson, 2009).

Major faults

A major geological feature that influences the orebody is the Kerril Fault, which is a broken zone of rock varying in thickness from 1–15 m. The structure is south of all stoping to a depth of 440 m below surface, after which the influence of the fault becomes noticeable. In addition to Kerril Fault is the Bayban Fault, a main fault structure that lies to the north of mining activities. The Kerril and Bayban Faults have the most significant impact on underground development at CUG.

The Kerril Fault is a late-stage reactivated dextral strike slip fault. It dips steeply with an orientation of $80^{\circ}/160^{\circ}$ and is characterised by a broken zone from 1–15 m in thickness (Basson, 2009). Stopes mined in proximity to the Kerril Fault are shown to overbreak into the fault zone. The Bayban Fault has sinistral movement displacing ore zones south, and is believed to be a conjugate of the Kerril Fault. It dips steeply with an orientation of $70^{\circ}/030^{\circ}$. The Bayban Fault is a large broken zone of rock formed by numerous shears, and varies

SCHEMATIC STRATIGRAPHIC COLUMN



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FIG 2 – Schematic cross-section through the stratigraphy.

in thickness from 5-20 m. The poorest rock mass conditions experienced at CUG are in the locality of the Kerril-Bayban Fault intersections. Table 1 summarises the rock mass characteristics of the CUG lithologies. Table 2 lists the major discontinuity sets as observed in the structural mapping data from underground.

Rock mass characteristics

The rock mass conditions at CUG are typically classed as 'good' to 'very good' based on the Q-system (Barton, Lien and Lunde, 1974), with some areas close to the Kerril and Bayban Faults classed as 'fair' to 'poor'. The rock mass conditions generally improve as they move from the Blake Beds to the Auron Host units (down through the stratigraphy), as shown in Figure 3. This aligns well with underground observations of the rock mass conditions. A summary of the rock mass conditions using Q-system and RMR for each lithology is shown in Table 1. The median, average and lower quartile values will be discussed later in the paper.

The most prominent discontinuity set at CUG runs subparallel to the Kerril Fault (64°/159°) and is pervasive throughout the mine. The second most prominent set is less steeply dipping at 35°/300°, and while it is recorded across all mining levels, it becomes more prominent with increased mining depth. A further set, 70°/028°, aligns well with both the dip and dip direction of the Bayban Fault, and becomes more prominent in development below 1220 m below surface and in the Lantin North orebody, where the Bayban Fault starts to influence mine access development.

Discontinuity surfaces are generally undulating and rough in texture, while planar and smooth joint properties become more prominent at lower levels of the mine (below 1220 m below surface). This is evident in observations of ground

TABLE 1 Summary of logged geotechnical parameters for each lithology. ROD SETS FF 0' RMR

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LAB Average 88 - 2.9 68.2 69.7 Lower quartile 86 - 3.8 25 62		Median	95	2	2.0	48	68
Lower quartile 86 - 3.8 25 62	LAB	Average	88	-	2.9	68.2	69.7
		Lower quartile	86	-	3.8	25	62

UBB: Upper Blake Beds; CBC: Callie Boudin Chert; MS: Magpie Schist; CLB: Callie Laminated Beds; LBB:Lower Blake Beds; LBL: Lower Blake Laminations; UAB: Upper Auron Beds; AB:Auron Beds; LAB: Lower Auron Beds

conditions in underground development. Discontinuity persistence of 2-4 m and spacing characteristics of 0.3 m-0.6 m remain consistent throughout the three main joint sets at CUG. Discontinuity infill and alteration properties also remain consistent (Doumis, 2014).

GROUND SUPPORT AT CALLIE UNDERGROUND MINE

Ground support studies

Past ground support and reinforcement analysis and design employed an empirical methodology (Lee, 1999; Pascoe, 2000; Pascoe, 2001) and a 'worst case wedge' approach. Following

TABLE 2

Summary of major discontinuity sets at Callie Underground gold mine.

Joint set	Dip (°)	Dip direction (°)	Average spacing (m)	Average trace length (m)	Surface characteristics
1 (Kerril-parallel)	64	159	0.5	3.6	Undulating rough
2	35	300	0.6	2.1	Planar rough
3 (Bayban-parallel)	70	028	0.7	3.3	Undulating rough



FIG 3 – Median Q' values of with lithology (stratigraphy is ordered from left to right).

this initial work, a comprehensive development ground reinforcement design was completed by Watson (2007), which adopted a design approach featuring empirical methods, probabilistic and conventional key block analysis and elastic numerical modelling. Probabilistic key block analysis was used to obtain the likely block sizes, and elastic numerical modelling was used to estimate the potential failure zone around development excavations.

Most recently, Doumis (2014) completed a structural analysis of the underground mapping data at CUG and is currently undertaking a ground support design assessment. This study follows a similar process to the work undertaken by Watson (2007) but consists of revised assumptions for stress, joint set orientations and properties and the key block analysis, due to the additional information collected with depth of mining over the past seven years.

Between 2007 and 2014, specific geotechnical assessments were conducted for minor changes to the ground support standards, such as intersection support (Graf, 2011), revised development dimensions and implementing a new mesh sheet size.

Current ground support regime

Development in the upper sections of the mine comprises ground support consisting of pattern and spot bolting with no surface support to a depth of approximately 600 m below surface. The bolts installed were either thread bar or point anchor and still remain in reasonable condition, with varying degrees of corrosion.

The current ground support regime employed in development comprises friction bolts and mesh to a prescribed pattern of 1.1 m collar spacing by 1.6 m ring spacing. Additionally, 6 m long twin strand cable bolts are installed in all intersections on either a 1.25 m \times 2 m or 2 m \times 2 m bolting pattern, depending on the type of intersection. In total, there are eight ground support profiles for development and a further five cable bolt designs issued for intersections and brow support.

Motivation for the ground support review

The two main driving forces that lead to this study were to ensure technical due diligence of the ground support system and potential cost improvements. Prior to the work conducted by Doumis (2014), an all-encompassing ground support assessment had not been conducted since Watson (2007). This provided an opportunity to compare the probabilistic and conventional key block analysis process with the DFN wedge analysis using FracMan[®] software. The ground support assessment had a specific focus to evaluate the bolt spacing in development and intersections and to determine whether reductions in support could be considered without comprising the safety of personnel or the integrity of the openings.

CONVENTIONAL DESIGN APPROACH

The CUG rock mass is considered to be a jointed and blocky rock mass, which is characterised by the nature and disposition of the discontinuities. The discontinuities close to the excavation define the surface block assembly and influence stability, as evidenced by the structurally controlled failures at CUG to date.

Predicting the coupled behaviour of a complete assembly of blocks is a complex problem limited by the current design tools. Generally, combinations of empirical and deterministic design approaches are used to design the ground support regimes in the underground mining environment. More advanced assessments of ground support requirements also consider the probabilities of occurrence. The discontinuities are often treated with the unrealistic assumption of rock wedges being defined by ubiquitous, infinitely continuous fracture planes (Rogers, Moffitt and Kennard, 2006). The presence of fractures in the rock mass is spatially variable, with their geometric, mechanical and hydraulic properties being more accurately described by statistical distributions.

Generally, all design philosophies require the following information (Dunn, 2010):

- description of the rock mass and identification of likely modes of failure
- assessment of demand/force (block size, depth of failure and support pressure required)
- assessment of capacity of the ground support elements
- acceptance criteria.

Empirical design process

Empirical ground support design is perhaps the most widely used approach in the mining industry due to the relative ease of use. This approach includes the use of design 'rules of thumb' and classification systems such as the Q-system (Barton, Lien and Lunde, 1974) and RMR (Bieniewski, 1973). These tools are useful to assist with ground support selection, particularly during the early stages of a geotechnical investigation. However, the engineer needs to remember that these charts were derived from civil engineering projects that are not always directly applicable to mining environments. Local experience is critical for the correct interpretation and application of these charts.

The most widely accepted empirical ground support design chart in Australia is the reinforcement category chart based on the Q-system. The chart is based on the assumption that the rock mass properties that dictate how the rock mass will behave when excavated are well represented by the Q-value. A rock mass with the same Q-value (regardless of the exact make-up of that rock mass) is predicted to behave much the same as any other rock mass with a similar Q-value. The chart has been in existence for almost 30 years, and Peck and Lee (2007) presented data from a number of case studies of mines in Australia showing that the actual support installed is markedly different to what the Q-system would have indicated.

In the authors' experience, it is common practice in the mining industry to approach these assessments using a particular percentile or quartile value for design (ie the lower quartile). The philosophy behind the lower quartile approach is that this more conservative estimate of the required ground support is suitable for approximately 75 per cent of the ground conditions encountered in these rock units. For the remaining 25 per cent, support upgrades may be required.

The Q-system rock mass classification scheme uses an indexing approach combining quantitative and qualitative data. As a result, linear quantities with anisotropic tendencies cannot be combined and fitted to a normal distribution statistical model where the sample base is assigned to a range of bins. A mean and standard deviation cannot be used to define a data set with a log distribution because it will bias the mean value towards the high end of the sample base.

Deterministic design

In the deterministic case, the orientation, length, spacing and nature of the discontinuities within the rock mass are directly sampled in the field and recorded. This sample of discontinuities is then used to estimate the size and geometry of potentially unstable wedges. The key to block analysis is understanding the three-dimensional size and interlocking of the rock blocks. The primary key block algorithms currently available are well documented, and the assessment of wedge stability underground typically uses the same basic approach.

Conventional wedge analysis (Goodman and Shi, 1985) can be used to assess the stability of removable blocks within a rock mass. The Unwedge[®] program (by Rocscience) applies these methods and can be used to analyse wedge failure around excavations in hard rock, where discontinuities are persistent and where stress-induced failure does not occur. The analysis is limited to using a single orientation value for a maximum of three discontinuity planes at any one time, and therefore requires multiple analyses on combinations of planes if more than the three discontinuity planes occur in the rock. The software creates the largest possible wedge from the three discontinuity planes that intersects the drive, while the user can scale the size of the wedges based on site experience and field observations. As this is a purely deterministic approach, it does not consider the range of wedge sizes that could occur and the likelihood that a particular wedge will occur. Therefore, this approach is considered a 'possibilistic' method as it identifies blocks that are possible but not necessarily probable.

Probabilistic key block design

Probabilistic key block analyses can be used to overcome some of the limitations imposed in deterministic analyses. Tools used for such analyses include JBlock (Esterhuizen, 1996) and SAFEX (Windsor and Thompson, 1992). JBlock was developed to evaluate the potential for gravity-driven rockfalls, and a probabilistic approach is used to determine the potential key block dimensions and their interaction with the installed support (Dunn, 2010). Using statistical values for the spacing, orientation and length of discontinuities, it is possible to estimate the occurrence of blocks within the walls of an excavation. Once the occurrence of blocks is known, simple key block analysis methods are used to evaluate whether blocks can be removed and whether the chosen support will be sufficient to ensure the stability of those blocks.

JBlock has some limitations in that it can only consider one surface at a time. Therefore, blocks that occur in the corners of the excavation are not considered and neither are random joints that can contribute to the formation of unstable blocks (Dunn, 2010). Likewise, SAFEX users are restricted to a single surface of blocks, and the program is largely used for the design of reinforcement for excavations in jointed rock based on identifying and stabilising all the blocks of rock that could form on the boundary of the excavation (Windsor and Thompson, 1992). The methodology that was proposed was based on the early developments in block theory supplemented with procedures for reinforcement design and assessment of unstable blocks.

DISCRETE FRACTURE NETWORK APPROACH

A DFN approach is a modelling methodology that seeks to build an explicit 3D representation of the natural fracture system in statistical ways. It does this by building a series of discrete fracture objects based on measured field observations of fracture size, orientation and intensity. The advantage of the DFN approach is its ability to capture the heterogeneity and uncertainty of the in situ rock mass and fracture state by explicitly and stochastically describing key elements of the system (Rogers, Moffitt and Kennard, 2006). This leads to the generation of geologically-realistic models based on and calibrated back to real data collected in the field. By deriving the fracture properties such as size and orientation stochastically and using Monte Carlo techniques to generate many samples of the network, a DFN approach can generate statistically valid series of representations of the actual data to constrain the likelihood of a particular outcome (Rogers, Moffitt and Kennard, 2006). This can then be used to develop a risk-based assessment of excavation geometry and support requirements.

The initial step in the methodology is to create an appropriate DFN model based on the site geological and geometrical models, and use drill hole and mapping data to condition this model. Using FracMan[®] software, the fracture geometry is not restricted to the smaller-scale elements and can include major structural fractures such as faults, fracture zones, dykes and stratigraphic contacts as deterministic elements (Moffitt and Rogers, 2007). Where fracture orientation data are highly systematic and organised into distinctive fracture sets, the statistical properties of these sets can be defined and used as a key stochastic input into the DFN model. If the data have a more dispersed orientation that does not support this approach, then an alternative method of 'bootstrapping' can be used. 'Bootstrapping' is a statistical method based on multiple random sampling with replacements from an original sample to create a pseudo-replicate sample of fracture orientations (Moffitt and Rogers, 2007). A degree of 'noise' is introduced to each sample to ensure that multiple realisations will result in a similar but not unique orientation model.

The preferred measure of fracture intensity for a DFN model is known as P32 (fracture area/unit volume), which is an intrinsic rock mass property. Whilst it cannot be directly measured, it can be inferred from the 1D and 2D data using a simulated sampling methodology (Rogers, Moffitt and Kennard, 2006). Although this is a simulated sampling method, a relationship can be developed between observed fracture intensity and the associated P32 value that allows the population of the model with the appropriate fracture intensity.

Figure 4 illustrates the difference between a DFN model built using the conceptualisation of the rock mass being comprised of infinite ubiquitous joints and a DFN model generated using stochastic parameters and realistic fracture properties.

Generating a discrete fracture network of Callie Underground

The generation of fractures at CUG is not trivial due to the complex folding of the bedding, which required further investigation into the controls on observed structures underground. A number of strategies were developed for generating the fractures to determine which methodology was most suitable for developing a geologically-realistic model of a particular level in the mine. These were:

- Bootstrapping based on existing structural information. While this was arguably the easiest approach, it ignores any possible dependence between bedding and fractures.
- Dividing the data into north and south limbs of the fold. If the data are divided between north and south dipping limbs, they could be split into two groups and generate fractures within two regions, one for each limb.

• A local coordinate system. This is a complex task involving the generation of a grid around the area of interest, the calculation of cell orientation and the generation of fractures relative to this. While this is possibly the most elegant strategy, it is also the most time consuming.

Before getting carried away with large-scale models, it was decided to focus efforts initially on the 340 Level, which was recently developed (Figure 5) and ready for stoping. This level was chosen due to the significant amount of geotechnical mapping and drill hole core logging that had been conducted and because the Kerril Fault was present in the southern sector.

Fracture orientation and fracture intensity were investigated along local drill holes and underground mapping data to study the effect of folding and faulting. To achieve this goal, intersections with faults and bedding planes were generated. Then, geotechnical core logging data was divided into subsets to visualise the differences in stereographic projections, cumulative fracture intensity plots and joint depth histograms. By undertaking this approach, the authors found that:



FIG 5 – Plan view of the 340 Level development and the location of the discrete fracture network (shown by the box).



FIG 4 – (A) Conceptual model of infinite ubiquitous joints; (B) discrete fracture network model constructed from realistic rock mass properties.

- The orientation of fractures is subparallel to major faults and appears to be independent to folding on this level. Indications of drag folding can be seen adjacent to faults. The preferred (and most simplistic) method for generating fractures is to bootstrap from the local mapping data. The orientation of structures can also be correlated to fault structures.
- Fracture intensity increases downwards in the stratigraphy and is less correlated with distance to faults. Detailed geotechnical logging was used to determine the geometrical mean of calculated P32 (area of fractures per unit volume of rock mass) and generate fractures between layer bounding stratigraphic surfaces.
- Fracture size appears to increase with depth down the stratigraphy. The size of measured structures appears to follow an exponential distribution, with different mean values for different units.
- The flat dipping features are present in each unit and probably have the smallest size. It is likely that flat features are under-represented in the mapping data set due to their orientation (subparallel with the 340 Level drive) and their small size. Therefore, their absolute intensity cannot be determined, but their relative intensity to other features is known based on mapping data.

Validating the discrete fracture network

A critical component of generating any DFN is the validation process. In order to verify that the model generated was representative of the actual physical data collected, a series of validation checks were undertaken on the data. Stereonet plots of fracture orientations were generated for the mapping data on the 340 Level and compared with the simulated fracture orientations generated from the DFN. The simulated data corresponded well with the actual data, as shown in Figure 6.

To validate the intensity of the generated DFN model, the fracture system was sampled with a simulated drill hole in exactly the same orientation as a geotechnical drill hole in close proximity. The P10 (fracture frequency or linear density) was then compared for the sampling borehole and the real borehole and showed good correlation (Figure 7).

The generated DFN fractures were traced along the wireframe of the 340 Level ore drive to assess the simulated trace length characteristics of the generated fractures in Figure 8. The trace lengths were measured and compared to the actual mapping data on the same level and also showed good correlation.

Based on these essential model validation checks, it can be asserted that the fracture network generated by the DFN holds true to the data used to define it.



FIG 7 – Comparison of linear intensity (P10) between actual borehole data and simulated sampling data.

Rock block stability calculations in FracMan[®]

Unlike other simple methods, the geometry of the excavations subject to the block stability analyses can be complete 3D shapes and are not limited to simple 2D tunnel profiles. Complex excavation geometries, such as underground workshops, crusher excavations, shafts, stopes and intersections, can be modelled. The DFN model is then sampled to determine the block-forming potential, and all full-forming wedges and blocks are identified.

The stability analysis for the blocks defined by the DFN is functionally identical to all other key block analysis tools. A fundamental difference is that the analysis is carried out for the defined blocks of a specific realisation of the fracture geometry, rather than on a combinatorial approach of infinite fractures. The stability analysis is then carried out by checking whether each block satisfies the criteria for unconditional stability, where the block may slide or whether it is free falling (Moffitt and Rogers, 2007). This approach therefore considers the probability of adverse wedge formation rather than just the possibility.

The rock blocks generated in the analyses can then be displayed by apex height and width, factor of safety, failure mode, stable versus unstable, volume, surface area, weight or support pressure required to keep the block from becoming unstable. Histograms and probability density functions can also be displayed using the same properties.



FIG 6 – (A) Stereonets of the mapped structural orientations and (B) the discrete fracture network simulated orientations.



FIG 8 – Comparison of measured and simulated trace length data.

COMPARISON OF RESULTS OF DIFFERENT METHODOLOGIES

In order to provide a comparison between the different methods, a single scenario of a 5 m high \times 5 m wide \times 30 m long drive was chosen.

Using the structural data from the underground mapping (Table 2), a simple block kinematic analysis was conducted using Unwedge[®]. The data was assessed in a couple of ways to obtain trace length and apex height information. Firstly, an analysis was completed without applying any constraints (ie no limits on trace lengths or apex height). This produced a roof wedge of approximately 25 t with an apex height of 3.44 m. The second scenario considers the 'upper quartile value' of

trace length measured in the mapping, and this represents the maximum allowable trace length for the kinematic assessment. In addition to scaling the trace lengths of the wedges, the apex height was constrained to approximately half the width of the maximum excavation span. This is an accepted rule of thumb that is based on the natural arch effect that occurs above an excavation and the zone of lower confinement that occurs below the arch. This produced an unstable roof wedge of 4 t and an apex height of 1.8 m.

For the JBlock analysis, the parameters were entered according to the mapping data in Figure 9. This scenario was simulated three times with various apex heights before varying the joint trace lengths and joint spacings to assess

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Joint 3	57	285	25	0.9	0.3	3	2.8	0.7	15		Г
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Joint 5	62	055	20	0.9	0.2	4	3.3	0.7	10		Г
Joint 6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
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FIG 9 – Parameters used in JBlock analysis.

the effect of these parameters on the apex height. Table 3 shows the results of the 12 simulations of the 5 m \times 5 m drive with the apex height and a brief description of the change in variables. The results of these simulations indicate considerable variability in the potential apex heights for the orientation data. As indicated by the amount of reiterations required, some interpretation and familiarity of the rock mass is required by the user to determine appropriate values for the ground support assessment.

The rock block analysis was run for one realisation in FracMan® based on the parameters previously defined. An example of the output of the rock block formation around the development is shown in Figure 10, and the distribution graphs are shown in Figure 11. This simulation indicated that the 95 per cent percentile of the apex height was 2.1 m compared to Run 12 in the JBlock analysis of 1.95 m. With both analyses indicating similar apex heights, a high level of confidence is gained to use an apex height of approximately 2 m for the ground support design assessment. For a direct comparison, an apex height of 1.95 m in the FracMan® analysis corresponds to the 94 per cent percentile. The benefit of the distribution graphs generated as part of the FracMan® analysis allows the practitioner to quickly assess the apex height (or width) and cumulative distribution of the data set. The FracMan® analysis could then be run in various drive orientations throughout the level to develop a risk-based assessment of excavation areas and support requirements, and then expanded further to incorporate intersection support requirements.

TABLE 3 Summary of JBlock simulations.

	Apex height (m)	Comment
Run 1	2.0	Exact mapping parameters
Run 2	1.5	Exact mapping parameters
Run 3	1.2	Exact mapping parameters
Run 4	1.5	Doubled joint spacing mean, min and max
Run 5	2.5	Doubled joint length mean, min and max
Run 6	3.0	Doubled joint spacing and joint length mean, min and max
Run 7	2.0	Doubled joint length mean only
Run 8	2.5	Doubled joint length mean and max only
Run 9	2.0	Doubled joint length mean only
Run 10	3.75	Doubled joint length mean and max only
Run 11	1.5	Doubled joint length max only
Run 12	1.95	30% increase in mean length and doubled max length

CONCLUSIONS

The real benefit of the DFN approach is that it accurately represents the 3D fracture network geometry. In the past, one of the barriers to using discrete modelling methods was the lack of accurate data describing the fracture geometry and its physical properties. However, over the last few years, there have been significant improvements in the ability to measure properties of the fracture network. This means that many sites are now collecting data that can be readily input into the DFN modelling process. The only hurdle for site engineers to overcome is to learn and understand the functionality of the FracMan[®] software. This process is currently underway at Newmont's Tanami operation, which is also developing a site-specific set of guidelines to assist geotechnical engineers in creating accurate DFN models.

A key advantage of the DFN approach is the ability to handle the analysis and results in a probabilistic way for use in design studies. Multiple realisations of the same model can be generated, with the stability analysis carried out on each iteration. The DFN model can be generated a large number of times (ie 100) and the stability analysis undertaken on each model, resulting in the generation of probability density functions of wedge mass, wedge volume, factor of safety and so forth (Rogers, Moffitt and Kennard, 2006). As seen in the comparisons of the different results produced from the various methodologies, the quantification of a probability of occurrence is crucial to providing a robust and rigorous ground support design.

This probabilistic approach using measured fracture size and orientation data effectively allows the engineer to apply an appropriate level of conservatism to the design application. In effect, the method can predict the likelihood of an unstable wedge occurring over a given area or volume of development. For instance, the results may predict the probability of a wedge greater than 3 t being present for every 500 m of drive length. This could also be expressed in terms of frequency of occurrence such that on average, a wedge greater than 3 t should occur every 1500 m.

The analysis of the fracture network in a discrete way allows the engineer to optimise appropriate measures for the specific fracture network. For instance, support systems such as bolt length, spacing and orientation can be optimised to provide the most effective support system to meet a given design criteria. The next step in the process would be to run a Monte Carlo simulation to generate multiple realisations of the DFN and run the subsequent rock block analyses to confidently apply a risk profile to different development orientations and areas at CUG.



FIG 10 – Results of the rock block-forming analysis in FracManTM.



FIG 11 – Histograms and cumulative distribution graphs of apex height and apex width from FracMan[™].

ACKNOWLEDGEMENTS

The authors would like to acknowledge the dedication of Frans Basson to improving the geotechnical knowledge and methods in the mining industry. Newmont Asia Pacific is also acknowledged for allowing the details of this paper to be published.

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