A STUDY OF BIASES, ASSUMPTIONS AND PRACTICAL CONSIDERATION FOR THE USE OF DISCRETE FRACTURE NETWORKS IN GEOMECHANICAL PRACTICE

by

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Abstract

The use of Discrete Fracture Networks (DFNs) is becoming increasingly common in geomechanical practice in addition to their continuing role in hydrogeology. These models can serve as useful tools for estimating interconnectedness of fractures, leading to estimates of probable block sizes and shapes for a set of input parameters. However, the development of these models is reliant on assumptions made about collected field data and while constructing the model themselves. The implications of these biases and assumptions are not well documented.

This work investigates the variables involved in building a Discrete Fracture Network model in order to provide insight into the decisions and assumptions made during the modeling process. Select assumptions required within the FracMan DFN software pertaining to model selection and construction are evaluated; biases and assumptions relating to field data and how it is collected that may impact the development of DFN input parameters are investigated and limits of the effects of these models on block sizes are determined. The parameters determined to be critical in determining the overall geometry of the fracture network are ranked according to their relative importance in DFN modelling and according to the relative accuracy of each parameter. This ranking is shown below.

<table>
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<th>Source</th>
<th>Oriented Borehole</th>
<th>Down-hole camera</th>
<th>Scanline Mapping</th>
<th>Window/ Bench Mapping</th>
<th>Circular window Mapping</th>
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<td>High to moderate</td>
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Chapter 1

Introduction

1.1 Project background and overview

As numerical simulation tools for geotechnical analysis and rock engineering become more sophisticated and powerful, reliance on empirical rockmass characterization tools becomes less necessary and less appropriate for advanced analyses. The ability to model structural complexity, however, is only beneficial if the network generation and structural properties are representative of the in situ conditions. The inherent challenges in field data collection that impact our ability to fully characterize the structure and the rockmass are not reduced by our ability to produce more complex models. In this context, numerical and empirical techniques share the same limitations with respect to the need for an accurate representation of the structural character of the rock mass and the assumed joint properties. Discrete Fracture Networks can be used to create realistic representations of the fractures present in a rockmass. Generation of Discrete Fracture Networks (DFNs) relies on statistics to extrapolate, modify and expand collected data to produce a synthetic fracture network. Collected data may be manipulated to produce models that appear realistic; however, they may not represent a reasonable approximation of the actual rock mass. DFN model realizations serve as explicit representations of fractures of finite size in 2D or 3D space and can be used to simulate discontinuities in a synthetic rock mass. Though important fractures (e.g. known faults, very large fractures) located at a given site can be included explicitly in a DFN, the DFN is primarily used to stochastically generate fractures of finite size at fixed, random locations within the model from a sampling of data. As the fracture networks are randomly generated according to a range of input parameters and distributions, there are an infinite number of different, but equi-probable realizations that can be generated to match a given
set of input parameters. Multiple realizations are therefore required to provide a, reliable output when doing DFN analyses. The number of realizations required is dependent on the size of the model relative to the mean blocks size and to the overall scale of the fracture network itself; this is discussed further in Chapter 2.

As with any attempt to represent real, complex information with simplified models, it is important that the effect of any of the assumptions necessary along the way be understood.

To create Discrete Fracture Networks suitable for rock mechanics applications requires the modeler to consider both the limitations of the chosen DFN model as well as the biases inherent in the data set on which a model is to be built.

Typical inputs to a DFN include:

- fracture (or fracture set) orientation;
- size and size distribution;
- intensity;
- spatial variation (zones of more or less fractured rock, grouped as separate geotechnical domains);
- persistence (i.e. the probability any given fracture will extend beyond another set); and
- aperture.

Additionally, permeability values may be incorporated if fluid flow is being examined; fracture surface strength values may also be applied to evaluate block stability along a boundary. These inputs are given defined distributions and are used to stochastically generate networks of discrete fractures in space. As such, a DFN seeks to be representative of a given rock mass in probabilistic terms, not to predict the precise locations of major structures, blocks, instability, etc.
1.2 Thesis objective and scope

The primary goal of this work is to evaluate the use of DFNs in rock mechanics applications. As the inclusion of DFNs as part of rock mass modeling becomes more prevalent in rock mechanics applications, it is important to understand the advantages and limitations of using these models. The impacts of assumptions that are made in the field while collecting data, while analyzing and evaluating that data prior to and during modeling work are considered and evaluated in this thesis, focusing on parameters that control the fracture network geometry. The validity of these types of models is evaluated by comparing generated models not only to the input data, but also to observations made on sites as excavations progress.

For the purposes of this work, the terms fracture and discontinuity are used interchangeably and refer to any naturally induced planar structures within a rock mass irrespective of origin. This includes, but is not limited to: joints, shears, faults, bedding and foliation.

Discrete fracture networks provide a method for evaluating theoretical fracture systems where all parameters are known. As such, the relationship between sampled data and the actual underlying system can be compared and existing assumptions about bias can be tested. As part of this work, both 1D and 2D sampling methods are compared to the 3D network.

Though the output results may match the input statistics, visual inspection may indicate incongruences between the real and modeled rockmasses, thus the importance of visually comparing the in-situ rock to the virtual results is stressed; suggestions for input selection and output validation are made as part of this work.

Smaller rock mechanics projects may not require or allow a full DFN simulation. A simplified characterization methodology based on block size distributions derived from DFN results is presented here to allow block size estimation from site data without conducting any new modeling work. This is compared to an existing rail cut for validation.
1.3 Thesis outline
This manuscript has been prepared according to the guidelines set out by the School of Graduate Studies and Queen’s University, Kingston, Ontario, Canada. The thesis is divided into the following chapters:

Chapter 2 provides a summary of background information from preliminary research prior to completing the main body of this work, focusing on systems of collecting and analyzing data as well as classifying rockmasses, with particular focus on fracture size and spacing measurements.

Chapter 3 provides details of the FracMan code inputs with examples illustrating the relative importance of the input parameters and necessary model assumptions required for creating a DFN for geomechanical purposes.

Chapter 4 discusses the relationship between collected data and model biases, focusing on the effects of limited data collection, and the biases inherent in attempting to define a 3D network through information collected in 1D or 2D. This chapter relies, in part, on material previously presented as part of refereed conferences.

Chapter 5 presents a suggested outline for classifying a rockmass according to its blockiness and an estimate of mean block size, determined from fracture size and spacing data. It is based largely on a paper submitted to the American Rock Mechanics Association 2014 Conference.

Chapter 6 provides a test case from photogrammetric data. DFN models are used to compare various data collection methodologies and to validate the theoretical data presented in Chapters 4 and 5. This chapter was prepared, in part, for submission to the DFNE 2014 conference, with photogrammetric data input from Cara Kennedy.

Chapter 7 summarizes the main conclusions from this thesis and provides recommendations for future work.

1.4 Summary of findings
The main findings of this work are summarized in the section below.
1.4.1 Extent of models
As much of this work uses block size distributions as a way to compare the impact of adjusting parameters within the model, it was also important to evaluate the limit of “edge effects”, or, in this case, the model size that was most likely to produce consistent block size distribution results through multiple realizations, while also minimizing the computing power required. It was found that the minimum model size depended on the expected block size for a rock mass; a more massive rock with few persistent fractures can produce large blocks and therefore requires a large model space to capture this behavior whereas persistent, closely spaced fractures create more uniform small blocks that require a smaller volume relative to the average block size to capture the characteristics of the rock mass. A model volume with edges 20 times the mean spacing is suggested as a minimum. It was also noted that running multiple realizations at a smaller scale resulted in more variability in output block size distributions while a larger sampling space produced more consistent results.

1.4.2 Effect of Fracture Size
Fracture size and intensity are linked in DFN model creation, as is often the case in real rock masses. For a discontinuity set of known intensity and an assumed fracture size, FracMan will produce more, smaller fractures or fewer larger fractures to satisfy the input intensity, resulting in approximately equal total fracture surface area. This has an effect on blocks formed (or connectivity of fractures), depending on the ratio of set spacing to mean length. Fractures that are long relative to the average spacing produce many small blocks limited by the spacing between fractures; shorter fractures produce fewer total blocks, though these can be larger on average if the fractures intersect one another; fractures that are very short, relative to the intensity, are less likely to intersect each other and produce very few blocks limited by the length of the fracture. If the assumed fracture size is within an order of magnitude of the average spacing, results can be very sensitive; however, as the ratio of fracture area to spacing increases, block size results
become increasing less sensitive. It was found that fractures having a mean fracture radius greater than 10 times the mean spacing could be considered continuous; that fractures larger than this did not change the total blockiness measured, while when fractures are smaller, on average, than 10 times the mean spacing, the total blockiness is sensitive to the fracture size input.

1.4.3 Effect of Intensity
The intensity, or degree of fracturing in a rockmass, is a parameter that is straightforward to measure in 1D - along a borehole or a scanline. In 2D, several methodologies for measuring spacing or intensity exist. Though these parameters are relatively straightforward to measure, they are directionally biased. Determining the overall 3D intensity from 1D or 2D data requires making several assumptions. As described above, if the intensity is changed while holding fracture size constant, there is a significant impact on expected block size when the size and intensity are within an order of magnitude. Block size is dependent on intensity when fractures are long; therefore the model is sensitive to the intensity parameter for comparatively long fractures, and becomes less sensitive for more massive rock masses with short, widely spaced discontinuities.

It is shown that for most distribution types considered, the estimate of 3D intensity (P₃₂) proposed by Wang (2005) is a reasonable approximation of the fracture intensity; producing results within 10% of the expected value even when the limitations on the approximation included in Wang (2005) are not met.

1.4.4 Effect of Distribution Type
As the underlying 3D distribution of fracture size is very difficult or impossible to verify, it becomes necessary to make an assumption about the distribution based on what can be observed. This is further complicated by the fact that distributions observed in 1D or 2D sampling may or may not be the same as those of the 3D network. Normal, lognormal, power law and negative exponential distributions were evaluated. It was found that distributions had little impact on
block size distributions when the fracture size was large compared to the intensity. When shorter, more widely spaced fractures were modeled, a negative exponential distribution could result in a mean block volume more than 16 times greater than for a normal distribution with the same mean fracture size and spacing. For the same model, the largest blocks were up to 32 times larger for the negative exponential distribution than for the normal, lognormal or power law distributions. The negative exponential distribution allows for some very large fractures to be generated, even when the mean is small. While power law and lognormal distributions could have similar characteristics, the distributions considered in this work had truncated tails. Many small blocks and some large ones can be formed due to the presence of a small number of continuous fractures, thus the presence of these large fractures can have a significant impact on the overall blockiness of the rockmass. Expected block size distributions were not very sensitive to distribution type for most other cases.

1.4.5 Biases from 2D sampling
It was found that the mean trace length for the models measured was between about 1.4 and 1.6 times the mean equivalent radius for the normal, lognormal and power law distributions. The negative exponential distribution produces trace lengths that are 2.2 to 3.5 times larger than the mean equivalent radius. This occurs due to the inherent bias towards sampling larger fractures, compounded by the fact that in the sample space, fractures were counted each time they intersected one of the 48 sample planes, which could be up to 48 times for the largest fractures. While this is an extreme example of sampling the same fracture multiple times due to the close proximity of the sample planes used, a similar sampling bias can occur in practice where the same fracture is mapped multiple times in adjacent sampling windows, but counted as a new fracture each time. The resulting fracture size estimate thus tends to be somewhat larger than the true value.
Truncation of large fracture traces has the opposite effect, and explains why the mean trace length was not larger for all of the distributions sampled.

1.4.6 Biases from 1D sampling
Borehole fracture frequency and RQD measurements were compared for a range of borehole orientations. It was found that, at some sampling orientations, the negative exponential distribution produced a fracture frequency up to 40% more than the expected value assumed for continuous fractures. This discrepancy became smaller as fracture size increased. A similar deviation from expected values was not observed in the other distribution types; the measured values were in agreement with the expected values.
The RQD measurements showed that, for the range where RQD is sensitive (mean spacing <0.3 m), it is a more consistent estimator than fracture frequency as it is less subject to orientation bias. The 0.1 m intact block length effectively acts as a buffer when determining the quality of the rockmass being examined.

1.4.7 Characterization of rockmass blockiness
One aspect of rockmass classification that has not been dealt with extensively is the block size distribution. Though approximations for “average” block size are common, these are seldom appropriate for design and only provide a very general idea of what can be expected. This work compares those existing equations to DFN model outputs and attempts to create block size distribution curves for the ratio between the average fracture area and the average spacing values.
It is shown that when mean fracture radius is more than 10 times the mean fracture spacing, the average block size is equal to about 1.6 times the cube of the mean spacing. For fracture sizes smaller than 10 times the mean spacing, block size is sensitive to the ratio between the fracture size and fracture spacing.

1.4.8 A Test Case Using Photogrammetry
To compare the outputs for various sampling methodologies and to test the validity of the block size estimates developed in Chapter 5, data sets derived from a photogrammetric scan of a slope are used to generate DFN models. The models are then intersected with surfaces with orientations similar to the measured face to produce a range of block sizes. The results from each set are compared with each other and with empirical estimates of block size.

It was shown that photogrammetric data tends to skew fracture size data towards smaller fractures. This is particularly pronounced in semi-automatically detected faces when compared with manually selected fractures.

The rockblocks generated in this analysis did not compare well with existing empirical block size estimates; however, estimates from the methods developed in Chapter 5 were found to produce reasonable agreement with the generated blocks.
Chapter 2

Literature Review

It has been shown that the presence of fractures in a rock mass can have significant impact on rockmass behavior, governing fluid flow and failure mechanisms as well as impacting overall strength parameters (Hoek, 1990; Cai et al., 2004; Elmo and Stead, 2010). Details about fracture or discontinuity geometry and condition can therefore be critical when characterizing a rockmass and are essential for constructing a Discrete Fracture Network (DFN) model. The following chapter provides some background on the discontinuity parameters that are typically collected, possible methodologies for data collection and analysis and a brief description of the challenges and limitations of the methods currently in common use.

2.1 Fracture Orientation and Fracture Set selection

Fracture orientation refers to the strike and dip or dip and dip direction of the plane of the fracture, measured with respect to horizontal and cardinal directions. Measurement is usually straightforward and can be done with relative ease in most cases. If the orientations of fractures or fracture sets are known, the sampling biases due to orientation are reasonably well understood and can be accounted for (Terzaghi, 1965; Hudson and Priest, 1979).

Though orientation can be measured and adjusted through widely accepted methodologies, the grouping of fracture data into sets, typically based on fractures with similar orientation, is more subjective. Several methodologies exist for grouping poles together including manual delineation and computer clustering algorithms. Manual set selection allows experienced personnel to incorporate knowledge of local fracture systems into set selection, but may introduce a high degree of subjectivity. Alternatively, computer codes are more objective but may not be able to distinguish complex patterns. Further, set selection can be more difficult or can produce
meaningless results if orientation data is not appropriately grouped according to geotechnical domain, where appropriate, and weighted according to orientation bias prior to set selection.

For ease of interpretation, it is often assumed that orientation data follows a standard distribution, such as a Fisher or Bingham distribution. Baecher (1983) showed that the orientation data for 22 sets available in the public domain failed to pass the $\chi^2$ or likelihood tests for Fisher, bivariate Fisher, Bingham, bivariate normal or uniform distribution types. However, the Bingham and bivariate Fisher distribution provided better fits than the other distributions in most cases. This is worth noting since nearly all set selection methodologies are dependent on the assumption that the data should follow a known distribution type. The theoretical models examined in this work assume a constant distribution; while this is not representative of real rock masses, it provides a simplified base case to which greater complexity can be added.

### 2.2 Fracture Size

Fracture size in this work refers to the total one-sided area of a single fracture surface within a rockmass. This is a simplified definition, as fractures are 3 dimensional structures that have both aperture and undulation into the third dimension; however, in most DFNs, they are treated as 2 dimensional planes in space.

In practice, fracture size is very difficult to measure as the limits of a fracture are not always visible and systematically dismantling a rockmass to examine the extent of the fractures contained within it would be costly and time consuming, if possible at all.

A fracture trace is formed by the intersection of a fracture surface with a mapping surface, creating a line. Though fractures are 3 dimensional features, the one dimensional trace length is the measurement that is most commonly available to describe fracture size. On a given mapping surface, a range of trace lengths may be observed; most often, these trace lengths will follow a lognormal distribution (Hudson and Priest, 1979; Priest, 1995; Baecher, 1985; Dershowitz, 1988), though other distribution types are possible.
Figure 2-1: How interfering distribution types often approximate negative exponential curves (from Hudson and Priest, 1979)
If several different phases of deformation have been super-imposed on a given rockmass, and each phase of deformation imparted a different fracture size distribution on the rock mass, a negative exponential distribution is the most likely resultant distribution (Hudson and Priest, 1979). Several distribution types are shown superimposed on one another to show this graphically in Figure 2-1, above, taken from Hudson and Priest, 1979. However, because of size sample bias, the large numbers of very small fractures associated with a negative exponential distribution are not likely to be sampled, and the resulting trace lengths will follow a lognormal distribution. Of the data sets described in available literature, trace sizes are most often observed to follow a lognormal distribution (Dershowitz and Einstein, 1988; Baecher, 1983; Hudson and Priest, 1979).

The researchers discussing these biases have created various methodologies for minimizing them by examining the number of fractures with one, two or no midpoints (Kulatilake and Wu, 1984) or endpoints (Mauldon, 1998, Zhang and Einstein, 1998) contained within a mapping window of a known area and orientation. Kulatilake and Wu (1984) used rectangular windows to determine the mean trace length, though the calculation was dependent on a known fracture orientation distribution, and assumed that length and orientation are independent. The mean trace length estimator, $\mu_1$, for a rectangular window, parallel to fracture trace strike, can be calculated as follows:

$$\mu_1 = h \left( \frac{N + N_T - N_C}{N - N_T + N_C} \right)$$  \hspace{1cm} (1-1)

Where $N$ is the total number of traces intersecting the window, $N_T$ is the number of traces transecting the window, $N_C$ is the number of traces contained in the window and $h$ is the height of the window (from Mauldon, 1998).

This idea was expanded upon by Mauldon, (1998) and Zhang and Einstein (1998) who modified the calculation to account for any convex shape and using fracture endpoints rather than midpoints, as the latter cannot be located when a trace is censored. Mauldon’s calculation was
also independent of any assumption about orientation or size distributions, which is significant as the initial assumptions can be difficult or impossible to test. The expected number of traces for a convex sampling region can be calculated using the following equation:

\[ E[N] = \rho(A + \mu E[w]) \]  \hspace{1cm} (1-2)

Where \( E[N] \) denotes the expected number of traces that intersect the window, \( A \) is the window area, \( E[w] \) is the expected window width for all values of \( \theta \), shown schematically below in Figure 2-2 below, \( \rho \) is the fracture density, and \( \mu \) is the mean trace length.

The estimators of \( \rho \) and \( \mu \), \( \tilde{\rho} \) and \( \tilde{\mu} \) are defined as follows:

\[ \tilde{\rho} = \frac{1}{2A} (N - N_T + N_C) \]  \hspace{1cm} (1-3)

\[ \tilde{\mu} = \frac{A}{E[w]} \left( \frac{N + N_T - N_C}{N - N_T + N_C} \right) \]  \hspace{1cm} (1-4)

Figure 2-2: Schematic showing area of fracture centers for fractures of orientation \( \theta \) in the mapping window (from Mauldon, 1998)
Zhang and Einstein (1998) used a calculation similar to that proposed by Mauldon, but used a circular sampling window to simplify the area calculations and to eliminate the need to account for orientation bias:

\[
\mu = \frac{\pi(N + N_0 - N_2)}{2(N - N_0 + N_2)} C
\]

(1-5)

Where \(\mu\) is the mean trace length, \(N\), \(N_0\), and \(N_2\) are the total number of traces intersecting the window, the number of intersecting traces with no ends contained in the circle and the number of traces with both ends contained within the circle respectively, and \(C\) is the radius of the circle.

Of the three methods mentioned above, all require that the sample window extends far enough that some fractures terminate within the window. They also require the extents of the mapping window be known. Delimiting circular regions on a surface of interest takes extra time, which is not always available on tight construction schedules. Further, if mapping vertical or near-vertical faces, a window large enough to minimize biases may create access issues if the upper part of the window is beyond the reach of the mapper. Finally, if knowledge of the fracture size distribution type is required for use in DFN modeling, these methods do not provide that information on their own. As such, while these methods do reduce sample bias, they are not always practicable and the biases that exist when these methods cannot be employed remain. These are discussed in greater detail in Chapter 4.

2.2.1 Fracture Shape

Though fracture surfaces are 3 dimensional (Zhang and Einstein, 2010) having small-scale roughness and larger scale undulations as well as often having an aperture, fractures in 3D networks are often approximated as discs or planes having only 2 dimensional area or may be represented as pipes or conduits or 2 planes with an aperture to give a fracture volume. The waviness of the surface itself is generally accounted for separately, using roughness and/or waviness coefficients. Undulations and rock bridges across the surface of a fracture may appear
as a termination on a mapping surface, though in the third dimension the surface may be largely continuous. This poses a problem when mapping fracture size data, as it may be impossible to tell from surface traces if several short fractures or a single long one with rock bridges is being observed. Such a discrepancy could significantly skew trace length data. Figure 2-3 below shows commonly observed structures on a fracture surface. Of particular interest are the boundary joints which create en echelon fracture patterns when viewed in cross section. As described above, this has the effect of making the edges of a single fracture appear as many much smaller en echelon cracks, which can create uncertainty about where a fracture actually terminates.

Figure 2-3: Schematic showing (1) plumose and (2) ring structures; (3) radial and (4) boundary joints are also observed along the fracture edges. Taken from Bankwitz, 1965, in Zhang and Einstein 2010, with translations from the original German.
Cruden (1977) recommends measuring the fracture size both along strike and down dip to provide an understanding of the shape of the fracture. Kulatilake and Wu (1984) and Baecher (1983) found that the lengths in the strike and dip directions were approximately equal; however others have found variation in trace length distribution between strike and dip. Zhang et al, (2003) showed that the long axis of an elliptical fracture may not align with the strike or dip of a fracture, resulting in approximately equal measurements even when the discontinuities are elongated. This is shown in Figure 2-8 below.

Figure 2-4: Cases where fracture length is approximately equal along strike and dip directions but fracture is elongated (from Zhang, et al., 2003)
Zhang and Einstein (2010) divide fractures into two categories: restricted and unrestricted. Restricted fractures terminate on other fractures, while unrestricted fractures terminate in intact rock. Terminations against existing discontinuities results in rectangular or polygonal fracture shapes, depending on the overall fracture network geometry. Unrestricted fractures, those that terminate in intact rock, tend to have an elliptical shape. In homogeneous, isotropic rock, crack growth will be equal in all directions and produce circular unrestricted fractures. This has been observed in hydrofracturing lab experiments (Cleary, 1984 in Dershowitz and Einstein, 1988). However, as most rockmasses are heterogeneous and/or anisotropic, the rupture growth will deviate from circular and become elongated. For restricted fractures in layered rocks, it is found that fractures will propagate towards the bedding layers which arrest further growth and cause the crack tips line to split and propagate away from the line of fracture nucleation. As strike and dip are measured relative to present-day north and horizontal, respectively, fracture elongation should not be expected to be related to these measurements as fracture propagation would have progressed according to the stress conditions in the rock at the time of fracture formation. Thus determining fracture elongation should be considered useful both in determining present day fracture sizes and also to assist in inferring previous stress regimes. The reader is referred to Zhang and Einstein (2010) for a suggested method for calculating the orientation of the long axis of the fracture as well as the elongation ratio between the short and long axes. It should be noted that mapping on at least two faces with significantly different orientations is required to generate a reasonable estimate.

2.2.2 Equivalent Radii
In this work, equivalent radii will be used as the input parameter into DFN models. Though the generated fractures can take any shape defined by the user, the area of that shape will be approximately equivalent to a circle of the input radius. For example, a four sided fracture with an equivalent radius of 1 m, would have an area of approximately 3.14 m², and a side length of
about 1.77 m. Therefore a square fracture with an equivalent radius of 1 is neither inscribed nor circumscribed to a circle, but rather generated to produce approximately the same area.

Elongated polygonal fractures would be generated in a similar fashion.

### 2.2.3 Size Distributions

The size distribution of a fracture set can be very difficult to determine. Measuring a trace on a mapping surface seldom reflects the true extent of the fracture. The mapping plane rarely intersects a diameter, but rather a chord of a circular or elliptical fracture. Closely spaced fracture traces of similar orientation may be connected in the out-of-plane direction. Finally, sampling in 2D has the tendency to produce a lognormal trace distribution, in almost all underlying 3D size distributions (Baecher, 1983). This effect of size distributions is explored further in Chapter 4.

To generate a Discrete Fracture Network, typically, a size distribution is assumed for each set, though in some cases where bimodal distributions are present, it may be beneficial to create sub-sets within a group of the same orientation with different size parameters. Other parameters may also need to be grouped accordingly.

As described above, the most commonly observed fracture trace distribution is lognormal (Dershowitz and Einstein, 1988; Baecher, 1983; Hudson and Priest, 1979). However, a range of other distribution types have been observed, including exponential, hyperbolic and Gamma-1 (Dershowitz and Einstein, 1988).

### 2.2.4 Determining size from indirect means

It is generally not possible to measure fracture size from borehole sampling, thus the planar extents of fractures must be inferred from trace lengths and partially exposed surfaces if mapping has been done, or somehow inferred from what can be observed in boreholes.

Vermilye and Scholz (1994) showed that for very simple geological settings, specifically a single phase of extension, an aspect ratio between vein aperture and length could be estimated between $1 \times 10^3$ and $8 \times 10^3$. These values are roughly in line with the tensile strength of the rock.
considered. It was also found that some closure can occur along the veins, so these estimates may be considered a lower bound. Additionally, the aperture tended to vary over the length of the fracture, with the aperture closing towards the fractures tips. Vermilye and Scholz (1994) also state that the observed aspect ratio is dependent on rock type, which may reflect increases in ductility.

In the same study (Vermilye and Scholz, 1994), faults were found to have a constant of proportionality ranging from $3.6 \times 10^{-3}$ to $2.9 \times 10^{-2}$, which is in line with shear strengths of rocks being roughly an order of magnitude larger than the tensile strength. This variation indicates that the mode of fracture generation plays a role in the aperture to length ratio.

A study of chlorite/epidote in-filled joints by Segall and Pollard (1983) in the Sierra Nevada measured a scaling constant between $1 \times 10^{-4}$ and $5 \times 10^{-4}$; however, there was difficulty in measuring the length of fractures when en echelon fractures were observed towards a fracture tip, indicating that the fracture may be more continuous than an observed trace. The constant is smaller than those described above, which could be due to fracture closure, variance in rock strength, or variance in the regional stress regime resulting in a different fracture generation mode. Additional deformation episodes could also account for some of the discrepancy.

Hatton et al., (1994) argue that a universal scaling relationship would indicate a universal fracturing mechanism and that the aspect ratio would be governed by the fracture toughness and/or a constant yield stress. They point to the reactivation and re-opening of existing fractures in an active rift zone as evidence that a universal scaling constant in even slightly complex geological settings may not be feasible. The data from the Icelandic rift zone considered by Hatton et al.(1994), show that fractures can follow a complex genesis even in a very short period, in a relatively homogeneous area.

If these relationships are to be considered for estimating fracture length in boreholes, it must be noted that this is only useful for healed or partially healed fractures or if a downhole camera is
used to assess aperture, as fracture opening cannot be measured from broken core. The use of any of these ratios is also limited by not knowing if the portion of the fracture being sampled is a maximum value of the individual fracture. From the details presented in this section, it is assumed that, while fracture aperture provides information about the relative sizes of fractures on some sites, this should be treated as a high level, first pass estimate. The complexity of fracture history for any rock mass will make these estimates less reliable and these estimates should be used with caution.

2.3 Fracture Intensity

Fracture Intensity is a measure of total fracturing in an area. It generally combines the fracture density (the number of fractures on a line, or in an area or volume) with the size of those fractures. In DFN applications the notation to describe the dimensions of the measurement is $P_{xy}$, where $x$ is the dimension being measured in, and $y$ is the dimension of the measurement. For $X$, 1 denotes measurements taken along a line, 2 denotes measurements made on a plane, and 3 denotes measurements in a volume. For $Y$, 0 denotes point measurements, 1 denotes a measurement of length, 2 denotes an areal measurement, and 3 denotes a measure of volume. For instance, the number of fractures (the dimension of the measurement is a count, or of 0 dimension) on a line (the dimension being measured in is linear or in 1 dimension) is denoted $P_{10}$.

This term is interchangeable with fracture frequency, commonly denoted as $\lambda$, and these will be treated as equivalent terms throughout this work.

Following the same convention described above, the $P_{32}$ value for a rockmass is the total area (dimension of measurement is area, or 2D) of fractures within a volume (dimension being measured in is volume, or 3D). The $P_{32}$ value is often considered to be the preferred way of describing the fracturing of a rock mass as, unlike other intensity descriptors, it is non-directional and gives an indication of the amount of fracturing of a rockmass. However, the $P_{32}$ value is derived from directionally biased methods, so, while it is a better estimate of overall fracturing it
is still dependent on being able to compensate for known biases. A $P_{32}$ value is also non-unique; many small fractures or fewer larger ones can produce the same fracture area in a volume, but result in different sampling biases, different block sizes and ultimately different rockmass behaviour. The volumetric intensity measurement, taken alone, also provides no indication of the number or orientation of fracture sets which, along with the mean fracture size control the connectivity of fractures. Connectivity, in turn, controls block formation, block size, conductivity and possibly overall behaviour.

The relationship between fracture size and intensity, and the impact of variations in these values, are discussed further in Chapters 4 and 5.

### 2.3.1 Spacing and Fracture Frequency

Fracture frequency, $\lambda$, which is interchangeable with the $P_{10}$ parameter described above, is defined simply as the number of fractures over a given length (typically a metre, though other units can be used). The average spacing value is equal to the inverse of $\lambda$. As the mean spacing provides a more tangible idea of fracturing, it will also be used interchangeably with the fracture frequency or $P_{10}$ term throughout this work. Fracture frequency values are directionally biased, and may include all of the fractures in a network, or may be limited to the fracture spacing of a single fracture set. The definition of set spacing has been given as the distance between adjacent fractures measured along a line normal to the fractures (ISRM, 1978). This may differ from fracture spacing along a scanline which could incorporate fractures from all sets along the line, or could include the true spacing of fractures from the same set encountered along a scanline. An un-oriented borehole is limited to fracture frequency of all sets, measured along the sample line, as the true orientations of each fracture are unknown and cannot be measured.

Unless evenly spaced discontinuities dominate, most spacing combinations of evenly spaced, clustered and randomly positioned fractures will create a negative exponential distribution (Priest and Hudson, 1976). A sampling line is generally located randomly with respect to multiple
fracture sets, and therefore can be seen as a random sampling of spacing distances. Therefore, each small section of the sample line has a small but equal chance of intersecting a fracture. This definition is the same as that for a Poisson process, used in DFN-generating algorithms, and produces a negative exponential spacing distribution. Figure 2-5 illustrates this concept schematically.

Figure 2-5: Scanline of regularly spaced fractures and randomly spaced fractures, side-by-side (from Priest, 1993).

The most significant control on a linear fracture frequency measure is the relative orientation of the scanline to the discontinuity normal; with the true set spacing occurring along the normal, and no intersection of the set when the sample line is parallel to the surface. To estimate the fracture intensity that would be expected along a sampling line of a given orientation the following equation from Hudson and Priest (1979) can be used:

\[ \lambda_\theta = \sum \lambda_i \cos \theta_i \]  

(1-6)

It has been shown repeatedly that short sample lines can lead to significant error in estimation of set spacing (Priest and Hudson, 1976, Choi and Park, 2004, Sen and Kazi, 1984) and scanline
lengths of 20/\( \lambda \) to 50/\( \lambda \) have been recommended to minimize this bias. Priest and Hudson (1976) suggest that a minimum of about 200 measurements are required to establish a negative exponential distribution, while Sen and Kazi (1984) suggested that spacing estimates and true population value in simulated sets become almost equal when the scanline has a length of 20/\( \lambda \); and that little additional information is gained for significantly longer samples. It is also noted that short scanlines will always underestimate mean discontinuity spacing. This is illustrated in Figure 2-6, below.

**Figure 2-6:** Estimate of mean discontinuity spacing compared to true discontinuity spacing for different scanline lengths (from Sen and Kazi, 1984).

Karzulovic and Goodman (1985) suggested a least squares estimate of the true fracture spacing using multiple scanlines, and known set orientations:

\[
ET = \sum_{j=1}^{M} (\lambda_j - \sum_{i=1}^{N} \lambda_i \cos \theta_{ij})^2
\]  

(1-7)
Where $M$ is the number of sample lines or boreholes, $N$ is the number of fracture sets, $\lambda_i$ is the true frequency of each set, $\lambda_j$ is the measured total frequency for each borehole or sample line, and $\theta_{ij}$ is the angle between the set and the sampling line. If the orientations of the sampling lines cover a reasonable range, this appears to be a good estimate; however, when orientations are similar or sample lines are very short, the method produces inconsistent results (Choi and Park, 2004).

It has also been suggested that orientation sample bias can be reduced by using a circular scanline (Rohrbaugh et al, 2002). The method uses the number of fracture intersections with the circular perimeter ($N$) and the number of terminations inside the circle ($M$) combined with the known size of the circle to estimate fracture size and intensity. An illustration of $N$ and $M$ are shown in Figure 2-7, below. The method is similar to that proposed for trace length estimation described by Zhang and Einstein (1998), and summarized in section 2.2.3, above.

![Figure 2-7: Schematic showing intersections with the mapping circle (A) and endpoints contained within the mapping circle (B).](image)

Though they may be more difficult to set up, more time consuming to carry out, and may be more subject to size limitations than conventional scanlines due to height and access constraints when dealing with vertical faces, circular scanlines can produce fracture frequency estimates that minimize orientation, censoring and length biases that are independent of spacing distribution. As with straight scanlines, fracture frequency estimates from circular scanlines improve with
increasing circle size. Further, all the above examples have assumed a homogeneous fracture network, however Rohrbaugh et al (2002) found that visual inspection alone was not adequate to identify homogeneous domains, and that several circles over the area are useful in determining the extent of domains. Obviously, this method is not applicable to borehole estimates, but is useful for window or scanline mapping projects.

When window mapping, the definition remains the same, but can be much less straightforward in practice as there is no sampling line to follow. Figure 2-8 shows a common situation when window mapping, where many different spacing measurements are possible for the same fracture, depending on where the measurement is taken.

Figure 2-8: Schematic of possible spacing measurements for a single fracture (black arrows), and spacing between fractures of comparable size (red arrows). From Palleske et al., 2013.

The example illustrated above leads to a much more subjective value that may not be reproducible by different mappers or even the same mapper at a different point in time. Thus, while linear spacing estimation might not make use of all the information observable on an outcrop surface, it produces more consistent measurements. This is discussed further in Chapter 4.
2.3.2 Volumetric Fracture Count

The volumetric Fracture count, \( J_v \), was introduced by Palmstrom in 1996 and is defined as:

\[
J_v = \frac{1}{S_1} + \frac{1}{S_2} + \frac{1}{S_3} + \cdots + \frac{1}{S_n}
\]

(1-8)

Where \( S_n \) is the average spacing of the \( n \)th set.

\( J_v \) describes the number of joints intersecting a volume of \( 1 \text{m}^3 \). Random joints (i.e. fractures that do not belong to an identified set) can be incorporated according to the following relationship:

\[
J_v = \frac{1}{S_1} + \frac{1}{S_2} + \frac{1}{S_3} + \cdots + \frac{1}{S_n} + \frac{Nr}{5\sqrt{A}}
\]

(1-9)

Where \( Nr \) is the number of random joints in an area, and \( A \) is the area in \( \text{m}^2 \).

It is assumed that the fractures are through-going in the volume; therefore fractures smaller than 1 m are not included or are poorly accounted for.

2.4 A brief discussion about statistics in geotechnical applications

As DFNs are created through stochastic methods, much of this work relies on probability distributions and cumulative density functions to evaluate or describe data. Those used within this work are summarized in this section, with brief descriptions of where a given distribution type has been found to be relevant. The effect of distribution type on blockiness, fracture intensity and sample bias are discussed in greater detail in Chapters 4 and 5. It is worth noting here that there is often confusion when assigning distribution types, particularly between log normal and power law distributions. Both display “long tails” and plot as linear or near-linear on a log-log plot. As will be shown in Chapter 5, the distinction between the two may be largely inconsequential for DFN applications.

2.4.1 Negative exponential

The negative exponential represents the time (or distance) between events in a Poisson process. It is defined by \( \lambda \) which represents a rate parameter. When referring to intensity, \( \lambda \) (the rate parameter) is equivalent to the mean fracture frequency, also commonly referred to as \( \lambda \). When
fracture size distributions are under consideration, the mean size will be represented by $\mu$, even if the distribution follows a negative exponential distribution.

The mean and standard deviation are, by definition, equivalent in this type of distribution. As mentioned in section 2.2, above, when two or more distribution types are overlain, a negative exponential distribution is likely to result. Both fracture size and fracture spacing have been observed to follow this type of distribution. A typical probability density curve is shown in Figure 2-9, below, along with the corresponding cumulative density curve.

![Figure 2-9: Example of a negative exponential distribution probability curve (f) and cumulative density curve (F) (from http://en.wikipedia.org/wiki/Exponential_distribution).](http://en.wikipedia.org/wiki/Exponential_distribution)

### 2.4.1 Normal

The normal distribution is the distribution that represents the central limit theorem, where data tends toward some mean value (Montgomery et al, 2006). Most of the curve (99.7%) falls within 3 standard deviations of the mean. Thus smaller standard deviations produce narrower curves, while larger standard deviations produce wider curves. It is seen and used widely throughout many applications, and many people are familiar with this concept. While little evidence exists to support using a normal distribution to describe geological DFN input parameters (particularly fracture size and spacing), it is thought that less experienced users may choose this distribution because it is familiar and understood despite its poor applicability. This could be exacerbated by a limited data set where an insufficient sample size exists for meaningful interpretation of distribution type. Examples of normal distribution curves are seen in Figure 2-10, below.
2.4.2 Lognormal

In the lognormal distribution, the log of the variable of interest follows a normal distribution. As with a normal distribution, it is defined by a mean and a standard deviation; however, the lognormal can have much longer tail than the normal distribution. Many geological phenomena have been found to follow lognormal distributions, most notably fracture trace size distributions are found in a large portion of cases to follow this type of distribution. This does not necessarily indicate that the underlying fracture size distribution is also lognormal, however, as both negative exponential and lognormal fracture size distributions will produce lognormal trace distributions (Baecher, 1983; Deshowitz and Einstein, 1988).

Examples of lognormal curves are shown in Figure 2-11, below.
2.4.3 Power Law

A power law distribution is a scale invariant distribution that describes a slow decay, which means that events that differ greatly from the mean, while still rare, are frequent enough that they should not be ignored. The “long tail” represents this potential for infrequent, but extreme events to occur.

The scale invariance indicates that the patterns that can be generated from a power law are the same, regardless of the scale at which they are observed, much like fractal patterns observed in nature. Fault and fracture size distributions have been observed to follow power law distributions. Examples of power law curves are shown in Figure 2-12, below.

Figure 2-11: Example of lognormal curves with different means, and standard deviations (from http://en.wikipedia.org/wiki/Log-normal_distribution).
Figure 2-12: Example of power law curves for different exponents (from http://en.wikipedia.org/wiki/Pareto_distribution).

2.4.4 The Fisher Distribution
The Fisher distribution represents the distribution of orientation vectors for, in this work, a fracture set. It is defined by a mean value and a dispersion coefficient, κ, which quantifies the degree of clustering in the Fisher distribution; higher values indicate tighter clustering and a small angle between the mean value and other members of the set, while lower values indicate a wider angle and more scatter.

2.4.5 The Bootstrap
The Bootstrap is not a distribution, but rather a technique for extrapolating and/or verifying data. In simple terms, it assumes that a sub-sample of the sampled population will have an analogous relationship to the total sample population as the total sample population has to the true population. From that assumption, it is possible to artificially generate data which can be used in fracture generation or can be used to help better fit a given data set to a standard distribution type. FracMan can apply a bootstrapping algorithm to many properties, including fracture size and orientation.
2.5 Classification systems

When describing insitu rock, it is useful to have common descriptors that can communicate the quality of the rock in general terms, and/or with respect to specific applications such as tunneling. The following section summarizes the most widely used systems, including the most relevant updates, modifications and critiques of those systems.

2.5.1 Rock Quality Designation (RQD)

The Rock Quality Designation (RQD) was introduced by Deere in 1963 and has been widely adopted in rock engineering practice. It is defined simply as the sum of all intact pieces of core greater than 10 cm divided by the total length of core, presented as a percentage. This is shown schematically in Figure 2-13.

The same principal can also be applied to scanline mapping, where fractures encountered along the scanline are counted as breaks in the core, and tallying the spaces greater than 10 cm accordingly.

![Figure 2-13 Schematic representation of RQD measurement and calculation for a core run](from Deere, 1989)
Though RQD is easy to measure, error can be introduced by counting mechanical or drilling-induced breaks as fractures, and through measurement error, typically associated with measuring from the top or bottom of a fracture, at an oblique angle to the core axis, rather than the middle of the fracture. The direction of the measuring line or borehole can have a significant impact on the measured RQD value as well, particularly in anisotropic rocks. This is commonly illustrated by assuming the rockmass to be a collection of bricks slightly longer than the threshold value (10 cm) in one direction and slightly shorter than the threshold values in a normal direction. As a result, the RQD is either 0% or 100% depending on the sampling orientation. This example is shown in Figure 2-14.

**Figure 2-14: The “brick” model showing RQD as 0 or 100 depending on sample direction (from Palmstrom, 2005)**

This illustration of orientation bias uses sample lines that are poorly designed; they each sample only one fracture set. In practice, assuming some knowledge of the natural fracturing in situ, an investigation should be designed to optimize the number of fractures crossed, or, at least, to simulate the orientation of the proposed excavation(s) to help predict what can be expected to be encountered during construction. Thus the 0% or 100% problem can be avoided with some knowledge of existing fracturing and a well-oriented borehole. The effect of orientation bias should be recognized and, when possible, efforts should be made to account for this by sampling along multiple orientations and/or by designing the investigation program based on existing knowledge of the area.
Another example cited in Palmstrom (2005) is where fracture spacing is uniformly 9 cm or uniformly 11 cm, again giving 0% and 100% RQD, respectively, despite both patterns being nearly equal. Figure 2-15 below shows this scenario schematically. Though this is possible in theory, it is unlikely to encounter fractures spaced regularly at exactly 9 cm (or 11 cm) along a random sample line, especially over many runs. As described in section 2.3, above, a negative exponential distribution of spacings is what is most commonly encountered in practice. Even a rockmass with normally distributed fractures would display enough variation to make the cited example improbable, and the actual RQD values much closer to each other.

![Figure 2-15: Measured RQD for different fracture densities (from Palmstrom 2005)](image)

Choi and Park (2004) found that orientation of scanline mapping along the sub-horizontal tunnel walls could vary up to 24% from vertical drillhole logs in the same area. This problem may be related to orientation sampling biases, but these can be compounded if the sample line in the tunnel is short. Sen and Kazi (1984) showed that a scanline length of $20/\lambda$ or greater resulted in a scanline estimate approximately equal to the population value. For scanlines shorter than this, the measurements always underestimated the mean spacing of the population; therefore increasing the sample length increases the expected RQD value, particularly when spacing values are large. The threshold value of 0.1 m was somewhat arbitrary and it has been suggested that this cutoff value be altered for different projects. Some discussions about RQD criticize the use of 10 cm as the “threshold value” and suggest an optimized threshold for individual sites. Harrison (1999)
states that rocks investigated for engineering projects tend to have either high (>85%) or low (<10%) values while rockmasses within the RQD range of 40% to 60% are seldom encountered. Harrison (1999) developed a calculation to optimize the threshold value for a given rockmass, dependent on the maximum and minimum fracture frequencies encountered. However, this calculation seems to exaggerate orientation bias – producing the maximum range of RQD for the same fracture intensity over all sampling orientations. While this may be useful on some large projects to illustrate relative degrees of fracturing across a site, most experienced practitioners have a gut-feel for the 10 cm threshold and have an intuitive sense of a rockmass from the RQD value. Furthermore, it would be more useful to minimize the orientation bias and instead determine a “characteristic” RQD for a given degree of fracture intensity.

It is interesting to note that Harrison (1999) found that the average fracture spacing (assuming an exponential spacing distribution) of 5 cm in homogeneous, isotropic fracture network had an optimal RQD threshold value of 10 cm. Further, a 5 cm average spacing gives an RQD value of 41%; generally considered poor quality rock.

If an RQD value is required for comparison, input in to another classification scheme or for contractual reasons, it can also be estimated from the expected fracture frequency estimate for a given orientation described in section 2.3. An attempt was made to correlate Jv and RQD using the equations:

\[ RQD = 115 - 3.3J_v \quad \text{for } J_v \geq 4.5m^{-1} \]  \hspace{1cm} (1-10)
\[ RQD = 100 \quad \text{for } J_v < 4.5m^{-1} \]  \hspace{1cm} (1-11)

However, it was shown that the above equations correlated poorly in a majority of cases (Palmstrom, 2005).

To better understand why RQD continues to be used, and why it remains an effective classification tool in many applications, despite its detractors, it is helpful to look at fracture spacing generally. If we assume that each fracture set was generated by separate processes and
that their locations in space are unrelated to each other, then a systematic brick-like fracture pattern is unlikely, and a more random distribution of fractures along the sample line is probable. This is discussed in Priest (1993) and was shown above, in Figure 2-5. Along sample line A, the fractures appear regularly spaced, while sample line B through the same fracture pattern, at the same orientation, produces a random or exponential spacing distribution. Over a sufficiently long borehole, average conditions can be expected to emerge.

If RQD is being measured along a surface, effort should be made to locate the sample line along an orientation that intersects a representative selection of fractures and, where possible, to ensure that the sample line extends to about 20 times the mean spacing.

In addition to being easy to measure, and less prone to measurement subjectivity, RQD is incorporated into other classification systems as part of an approximation of block size. Further discussions on RQD sampling bias are found in Chapter 4.

2.5.2 The Q System

Developed by Barton et al. in 1974 based primarily on experience in tunnelling in Norway, the Q system incorporates 6 factors for rockmass characteristics to give a value between 0.001 and 1000. Q is calculated as follows:

\[
Q = \frac{RQD}{J_n} \times \frac{J_r}{J_a} \times \frac{J_w}{SRF}
\]

where RQD is the rock quality designation, Jn is a joint number factor, Jr is a rating for joint roughness, Ja is a rating for joint alteration, Jw is a rating for water and SRF is a strength reduction factor. The ratings for each of the factors are shown in Figure 2-16 and Figure 2-17.

If each of the quotients is examined individually, they represent: a rough estimate of block size; a factor for fracture strength characteristics; and the in-situ stress regime.

Of particular interest to this work is the block size estimate (RQD/Jn). As much of this work examines block size estimation techniques it is worth noting the level of importance this factor is given as well as the level of detail used in its calculation.
<table>
<thead>
<tr>
<th><strong>DESCRIPTION</strong></th>
<th><strong>VALUE</strong></th>
<th><strong>NOTES</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>1. ROCK QUALITY DESIGNATION</td>
<td>\textit{ROD}</td>
<td>1. Where ROD is reported or measured as ( \leq 10 ) (including 0), a nominal value of 10 is used to evaluate ( Q ).</td>
</tr>
<tr>
<td>A. Very poor</td>
<td>0 - 25</td>
<td></td>
</tr>
<tr>
<td>B. Poor</td>
<td>25 - 50</td>
<td></td>
</tr>
<tr>
<td>C. Fair</td>
<td>50 - 75</td>
<td></td>
</tr>
<tr>
<td>D. Good</td>
<td>75 - 90</td>
<td>2. ( \text{ROD intervals of 5, i.e. 100, 95, 90 etc. are sufficiently} ) accurate.</td>
</tr>
<tr>
<td>E. Excellent</td>
<td>90 - 100</td>
<td></td>
</tr>
<tr>
<td>2. JOINT SET NUMBER</td>
<td>( J_c )</td>
<td></td>
</tr>
<tr>
<td>A. Massive, no or few joints</td>
<td>0.5 - 1.0</td>
<td>1. For intersections use ( (3.0 \times J_c) ).</td>
</tr>
<tr>
<td>B. One joint set</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>C. One joint set plus random</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>D. Two joint sets</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>E. Two joint sets plus random</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>F. Three joints</td>
<td>9</td>
<td>1. For intersections use ( (3.0 \times J_c) ).</td>
</tr>
<tr>
<td>G. Three joint sets plus random</td>
<td>12</td>
<td>2. For portals use ( (2.0 \times J_c) ).</td>
</tr>
<tr>
<td>H. Four or more joint sets, random,</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>heavily jointed, ‘sugar cube’, etc.</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>J. Crushed rock, earthlike</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>3. JOINT ROUGHNESS NUMBER</td>
<td>( J_r )</td>
<td></td>
</tr>
<tr>
<td>a. Rock wall contact</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>b. Rock wall contact before 10 cm shear</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>A. Discontinuous joints</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>B. Rough and irregular, undulating</td>
<td>1.5</td>
<td>1. Add 1.0 if the mean spacing of the relevant joint set is greater than 3 m.</td>
</tr>
<tr>
<td>C. Smooth undulating</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>D. Slickensided undulating</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>E. Rough or irregular, planar</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>F. Smooth, planar</td>
<td>0.5</td>
<td>2. ( J_r = 0.5 ) can be used for planar, slickensided joints having lineations, provided that the lineations are oriented for minimum strength.</td>
</tr>
<tr>
<td>G. Slickensided, planar</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>c. No rock wall contact when sheared</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>H. Zones containing clay minerals thick</td>
<td>(nominal)</td>
<td></td>
</tr>
<tr>
<td>enough to prevent rock wall contact</td>
<td>(nominal)</td>
<td></td>
</tr>
<tr>
<td>J. Sandy, gravelly or crushed zone thick</td>
<td>0.75</td>
<td>1. Values of ( \varphi' ), the residual friction angle, are intended as an approximate guide.</td>
</tr>
<tr>
<td>enough to prevent rock wall contact</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>4. JOINT ALTERATION NUMBER</td>
<td>( J_a )</td>
<td>( \varphi' ) degrees (approx.)</td>
</tr>
<tr>
<td>a. Rock wall contact</td>
<td>0.75</td>
<td>1. Values of ( \varphi' ), the residual friction angle, are intended as an approximate guide to the mineralogical properties of the alteration products, if present.</td>
</tr>
<tr>
<td>A. Tightly healed, hard, non-softening,</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>permeable filling</td>
<td>2.0</td>
<td></td>
</tr>
<tr>
<td>B. Unaltered joint walls, surface staining only</td>
<td>1.0</td>
<td>25 - 35</td>
</tr>
<tr>
<td>C. Slightly altered joint walls, non-softening</td>
<td>2.0</td>
<td>25 - 30</td>
</tr>
<tr>
<td>mineral coatings, sandy particles, clay-free</td>
<td>(nominal)</td>
<td>disintegrated rock, etc.</td>
</tr>
<tr>
<td>D. Silty, or sandy-clay coatings, small clay-fraction (non-softening)</td>
<td>3.0</td>
<td>20 - 25</td>
</tr>
<tr>
<td>E. Softening or low-friction clay mineral coatings, i.e. kaolinite, mica. Also chlortie, talc, gypsum and graphite etc., and small quantities of swelling clays. (Discontinuous coatings, 1 - 2 mm or less)</td>
<td>4.0</td>
<td>8 - 16</td>
</tr>
</tbody>
</table>

Figure 2-16: Parameter ratings for the Q classification system (from Hoek, 2007, after Barton et al. 1974)
4. JOINT ALTERATION NUMBER  
   \( J_a \) \( \phi \) degrees (approx.)

   **b. Rock wall contact before 10 cm shear**
   - F. Sandy particles, clay-free, disintegrating rock etc.  
     clay mineral fillings (continuous < 5 mm thick)  
     4.0  
     25 - 30
   - G. Strongly over-consolidated, non-softerning  
     clay mineral fillings (continuous < 5 mm thick)  
     6.0  
     16 - 24
   - H. Medium or low over-consolidation, softening  
     clay mineral fillings (continuous < 5 mm thick)  
     8.0  
     12 - 16
   - J. Swelling clay fillings, i.e. montmorillonite,  
     (continuous < 5 mm thick). Values of \( J_a \)  
     depend on percent of swelling clay-size  
     particles, and access to water.

   **c. No rock wall contact when sheared**
   - K. Zones or bands of disintegrated or crushed  
     rock and clay (see G, H and J for clay  
     M. conditions)  
     8.0  
     8.0 - 12.0  
     6.0 - 24
   - N. Zones or bands of silty- or sandy-clay, small  
     clay fraction, non-softerning  
     5.0
   - O. Thick continuous zones or bands of clay  
     P. & R. (see G, H and J for clay conditions)  
     10.0 - 13.0  
     6.0 - 24.0

5. JOINT WATER REDUCTION \( J_w \) approx. water pressure (kg/cm²)

   - A. Dry excavation or minor inflow i.e. < 5 l/m locally  
     1.0  
     < 1.0
   - B. Medium inflow or pressure, occasional  
     outwash of joint fillings  
     0.66  
     1.0 - 2.5
   - C. Large inflow or high pressure in competent rock  
     with unfractured joints  
     0.5  
     2.5 - 10.0
   - D. Large inflow or high pressure  
     0.33  
     2.5 - 10.0
   - E. Exceptionally high inflow or pressure at blasting,  
     decaying with time  
     0.2 - 0.1  
     > 10
   - F. Exceptionally high inflow or pressure  
     0.1 - 0.05  
     > 10

6. STRESS REDUCTION FACTOR \( SRF \)

   **a. Weakness zones intersecting excavation, which may  
      cause loosening of rock mass when tunnel is excavated**
   - A. Multiple occurrences of weakness zones containing clay  
     or chemically disintegrated rock, very loose surrounding rock any  
     depth  
     10.0  
     1. Reduce these values of \( SRF \) by 25 - 50% but  
     only if the relevant shear zones influence do  
     not intersect the excavation
   - B. Single weakness zones containing clay, or chemically disintegrated rock (excavation depth < 50 m)  
     5.0
   - C. Single weakness zones containing clay, or chemically disintegrated rock (excavation depth > 50 m)  
     2.5
   - D. Multiple shear zones in competent rock (clay free), loose  
     surrounding rock (any depth)  
     7.5
   - E. Single shear zone in competent rock (clay free), (depth of  
     excavation < 50 m)  
     5.0
   - F. Single shear zone in competent rock (clay free), (depth of  
     excavation > 50 m)  
     2.5
   - G. Loose open joints, heavily jointed or 'sugar cube', (any depth)  
     5.0

Figure 2-17: (cont’d) Parameter ratings for the Q classification system (from Hoek, 2007 after Barton et al. 1974)
Figure 2-18: (cont’d) Parameter ratings for the Q classification system (from Hoek, 2007, after Barton et al. 1974)

It is worth noting that, as described in Figure 2-18, the RQD parameter can be calculated from a Jv value when RQD values are not available, according to the equation (1-10), above, though the relationship between RQD and Jv has been shown to be unreliable (Palmstrom, 2005).

The rockmass parameters described in Figure 2-16 to Figure 2-18 are combined with the span and the end use of the excavation in question to provide support guidelines, as shown in Figure 2-19.
Figure 2-19: Reinforcement guidelines for different rock mass qualities, as defined by the Q system (from Grimstad and Barton, 1993, after Palmstrom and Broch, 2006)

The system has been subject to numerous modifications to extend the system to other applications. It should be noted that, as with RMR described below, the classification system is best used as a preliminary design tool, and that support re-design and optimization should be carried out, where warranted, as actual ground conditions are exposed during construction (Bieniawski, 1997; Hoek and Brown, 1980).

2.5.3 Rock Mass Rating (RMR)

The Rock Mass Rating system was first introduced by Bieniawski in 1976 and was updated with input from increasing numbers of case histories until an update of the RMR classification was published by Bieniawski in 1989. The system provides support guidelines based on a 10 m span, drill and blast, horse-shoe shaped tunnel based on the following factors:
- Rock strength (UCS or PLT)
- RQD
- discontinuity spacing
- discontinuity surface condition
- Groundwater
- Orientations of discontinuities

A rating number is assigned for each of the above parameters to give a value between 0 and 100, with 0 being very poor and 100 being very good rock. The rating values for each of the parameters are shown in Figure 2-20, below, taken from Bieniawski, 1989. The support guidelines are shown in Figure 2-21.

Because this classification system was primarily for use in tunneling for civil engineering projects, it was found to overlook many considerations typical of a mining environment, such as changing stress conditions.

In terms of accounting for discontinuities and block size, it is worth noting that RMR includes both RQD – a measure of the degree of fracturing – and fracture spacing – also a measure of the degree of fracturing. While these two parameters are not identical, they are very closely related and could be considered to be double counting the fracture spacing. The relationship between fracture spacing and RQD is explored in more detail in Chapter 4. It is also worth noting that fracture length is not directly accounted for in this system.
Figure 2-20: RMR classification parameters and associated ratings (after Bieniawski, 1989).
### Geologic Strength Index (GSI)

GSI was first introduced as a complement to the Hoek-Brown criterion to provide a method for classifying rock based on field observations (Hoek et al., 1995). At the time GSI was introduced, the existing classifications methods had been developed in a limited range of geological conditions, primarily for use in tunnel design and construction. GSI gave a range from about 10 for very poor rockmasses up to about 85 for very good rockmasses. A GSI of 100 was used for intact rock.

GSI was used to estimate the variables $s$, $a$, $m_b$, and $m_I$ to define the rockmass properties. These are defined as follows:

\[
s = \exp \left( \frac{GSI - 100}{9 - 3D} \right) \quad (1-13)
\]

\[
a = \frac{1}{2} + \frac{1}{6} \left( e^{-GSI/15} - e^{-20/3} \right) \quad (1-14)
\]
\[ m_b = m_i \exp \left( \frac{GSI - 100}{28 - 14D} \right) \]  

(1-15)

Where GSI is the value selected based on the criteria described in Figure 2-22, below, D is the disturbance factor with a value of 0 for undisturbed rock and 1 for very disturbed rock, and \( m_i \) is a material constant for the intact rock.

To allow comparison between GSI and existing classification system or as a secondary check on field observations, GSI and RMR\(_{76}^{'}\) and RMR\(_{89}^{'}\) are related as follows (from Hoek et al., 1995):

For \( \text{RMR}_{76}^{'} > 18 \)

\[ GSI = \text{RMR}_{76}^{'} \]  

(1-16)

For \( \text{RMR}_{89}^{'} > 23 \)

\[ GSI = \text{RMR}_{89}^{'} - 5 \]  

(1-17)

Low values of RMR (<18 RMR\(_{76}^{'}\) and <23 RMR\(_{89}^{'}\)) cannot be converted to GSI and the Q system is used instead according to the following relationship (from Hoek et al., 1995):

\[ GSI = 9 \log Q^{'} + 44 \]  

(1-18)

Additions to the low end of the GSI chart were made to include sheared and/or very weak rockmasses. The upper end was also raised from 85 to 100 to incorporate massive, intact rock (Hoek and Marinos, 2000). The chart is shown in Figure 2-22, below.

In an attempt to quantify and standardize the blockiness descriptor, a scale was introduced along the vertical axis of the chart by Cai et al. (2004). This included both a block size and a mean spacing scale. The mean spacing scale has allowed others to apply GSI ratings to core logs, based on an assumed blockiness as per Tzamos and Sofianos (2007).
Figure 2-22: GSI chart for estimation of Hoek-Brown parameters, from Hoek and Marinos, 2000.
Most recently, the chart was modified by Hoek et al. (2013) to return to the original range of GSI – from about 5 to 85 – to include numeric scales on the horizontal and vertical axes, and to adjust the lines on the chart such that they followed a linear equation. The horizontal axis uses the JCond₈₉ parameter from Bieniawski (1989), while the vertical axis uses RQD/2 as an approximation of block size. These modifications will be discussed further in Chapter 5.
Figure 2.23: Quantification of GSI chart (from Cai et al. 2004)
Chapter 3

Using Discrete Fracture Networks

As numerical simulation tools for geotechnical analysis and rock engineering become more sophisticated and powerful, reliance on empirical rockmass characterization tools becomes less necessary and less appropriate for advanced analyses. The ability to model structural complexity, however, is only beneficial if the network generation and structural properties are representative of the in situ conditions. The inherent challenges of field data collection that impact our ability to fully characterize the rockmass are not reduced by our ability to produce more complex models; a complex model is still only as good as the data it is based on. In this context, numerical and empirical techniques share the same limitations with respect to the need for an accurate representation of the structural character of the rock mass and the assumed joint properties.

Generation of Discrete Fracture Networks (DFNs) relies on statistics to extrapolate, modify and expand collected data to produce a synthetic fracture network. The data manipulation allows modified data to produce models that appear realistic; however, they may not represent a reasonable approximation of the actual rock mass.

This chapter introduces the FracMan code and the inputs required to build a geometric fracture network. The text should be seen as a complement to the existing user documentation to provide basic guidelines for DFN modeling in FracMan. Examples and justifications for various assumptions that are required during the DFN modeling process both throughout this work and elsewhere are examined.

3.1 FracMan Introduction

Though several DFN codes are available, the Golder Associates’ FracMan code was used for this research due to its availability and common use in industry.

The following types of fracture network construction are possible in FracMan:
• Geometric;
• Geocellular;
• Stratigraphic; and
• Trace Map.

This work focuses primarily on the geometric fracture generation algorithms which locates fractures in space based on the selected statistical distribution type until a given intensity is reached. Stratigraphic examples are not used in this work, but, for reference, they are generated by first create the stratigraphic fractures (bedding planes) and then defining fractures relative to the dominant features. Trace map and geocellular approaches were not used in this work and are not discussed here.

3.1.1 Geometric Fracture Networks

Geometric fracture networks can be used to represent any rock type, though the stratigraphic model is often simpler and/or more appropriate for rocks of sedimentary origin. To create a geometric fracture network in FracMan, one must choose between 3 generation models:

• Enhanced Baecher: fracture centers are located randomly, with uniform probability in space; fracture size is independent of fracture location.
• Levy-Lee: creates fracture centers sequentially, with fracture size related to the distance from previously generated fractures.
• Nearest Neighbour: Fracture Intensity decreases with distance from a user-defined zone or feature – appropriate for cooling margins, stress relief fractures and some fault zones.

This work focuses on Enhanced Baecher generation models as Poisson processes, indicated by negative exponential spacing distributions are most commonly observed in the literature (Priest and Hudson, 1976; Einstein et al., 1980, Baecher, 1983) as well as in other codes that incorporate DFN algorithms. The Levy-Lee and Nearest Neighbour models are not discussed further here.
3.1.1.1 Enhanced Baecher Input Parameters for Fracture Set Construction

The following input parameters are required to create an Enhanced Baecher geometric fracture network:

- Fracture Orientation;
- Fracture Intensity;
- Fracture Size;
- Fracture Shape; and
- Termination.

Each of these parameters is described in detail below.

Fracture Aperture, Permeability and Compressibility can also be input into the model to establish block stability or fluid flow, but these are not considered in this work.

3.1.1.2 Sources of Input parameters

The above-listed parameters must be measured, calculated or estimated from field data that can be acquired in a variety of ways, each having associated ranges and limitations. Values that are measured directly are the most reliable, with reasonably well understood biases and corrections. Values that must be calculated from measurements are reliable, provided the error in the input measurements is minimal and that the limitations of the equations being used are understood; however, some calculated parameters are based on estimated rather than directly measured values and have a lower degree of confidence. Values that are estimated have a lower degree of confidence as these are based on empirically derived relationships and/or the experience of the practitioner.

While some of the biases associated with this sampling are discussed in more detail in Chapter 4, they are summarized in Table 3-1, along with a range of data collection methods that may be used to collect them and a relative confidence rating for each. The parameters are ordered from most to least critical in defining a DFN model, and the best level of accuracy that can be achieved is
recorded (i.e. a parameter that can be measured directly can also be estimated is rated as having a “high” degree of confidence while a parameter that can only be estimated is rated as “low”).

The Circular window mapping refers to the methodology laid out by Rohrbaugh et al. (2002).

Table 3-1: Summary of input parameter sources and relative confidence of each

<table>
<thead>
<tr>
<th>Source</th>
<th>Oriented Borehole</th>
<th>Down-hole camera</th>
<th>Scanline Mapping</th>
<th>Window/ Bench Mapping</th>
<th>Circular window Mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orientation</td>
<td>High to moderate</td>
<td>High to moderate</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Mean set Orientation</td>
<td>High to moderate</td>
<td>High to moderate</td>
<td>High to moderate</td>
<td>High to moderate</td>
<td>High to moderate</td>
</tr>
<tr>
<td>Intensity/ Mean Set Spacing</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>High to moderate</td>
<td>High</td>
</tr>
<tr>
<td>Size</td>
<td>N/A</td>
<td>Low</td>
<td>Moderate to Low</td>
<td>Moderate to Low</td>
<td>Moderate</td>
</tr>
<tr>
<td>Shape</td>
<td>N/A</td>
<td>N/A</td>
<td>Moderate to Low</td>
<td>Moderate to Low</td>
<td>Moderate to Low</td>
</tr>
<tr>
<td>Termination %</td>
<td>Low</td>
<td>Low</td>
<td>Moderate to Low</td>
<td>High to moderate</td>
<td>N/A</td>
</tr>
<tr>
<td>Aperture</td>
<td>N/A</td>
<td>Moderate</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
</tbody>
</table>

Each of these parameters and their impact on DFN modelling are discussed in greater detail below.

3.1.2 Fracture Orientation

Fracture orientation is generally grouped into sets, with an average orientation (strike and dip) and a distribution around the mean orientation. Orientation is a relatively straightforward parameter to measure while mapping and, to a lesser extent, in oriented boreholes, where there
are increased sources of error. The most contentious part of using fracture orientation data may lie in determining the total number of fracture sets, which measurements belong in which set considering the range of dip and dip direction included in the set, and which orientation values should be considered to be characteristic of the rockmass.

Typical methods for determining set selection include manual selection from visual inspection; hand selection from weighted contour plots such as those produced in DIPS; and iterative clustering algorithms, such as those by Shanley and Mahtab (1976) and Mahtab and Yegulalp (1982), which examine weighted pole density over a stereonet. Manual selection allows complex systems and patterns to be detected by an experienced person, particularly if that person is familiar with the geology; automated selection is more consistent and less subject to bias.

FracMan has its own integrated set selection algorithm, Iterative Set Identification System (ISIS); however, this is not evaluated in this work. It is also possible to use orientation data without selecting sets by using the bootstrapping technique described in Chapter 2 on orientation data to create a larger population of data from which to generate fractures.

In addition to common orientations, additional parameters such as fracture size or infill can be used to identify sets, or to create sub-sets within a group of similarly oriented fractures if this is more appropriate for the work at hand. For DFN generation, grouping a set with bi-modal size distribution into two sets according to size may lead to a more representative model. Similarly, vastly different fracture properties within fractures of similar orientation, such as aperture or roughness may warrant creating separate sets to represent this variability rather than averaging the measured values. While some programs may allow a range of parameters to be applied to a surface, FracMan applies the same input strength parameters to all fractures considered when analyzing block stability.

For the conceptual models examined in this work, 3 sets with constant orientations of 000/85, 090/85 and 270/15 are used, unless specified otherwise.
3.1.3 Fracture Intensity

The terminology for fracture intensity in FracMan is described by $P_{xy}$, where $x$ is the dimension of the sampling region, and $y$ is the dimension of the measurement. For example, the count of the number of fractures (the measurement with dimension 0) measured along a borehole (the sampling region with 1 dimensional – length) would be denoted as $P_{10}$. The total length of fractures (1 dimensional) measured on an area (2 dimensional) would be denoted as $P_{21}$. This is shown schematically in Table 3-2, below.

As intensity input parameters, FracMan allows $P_{10}$, $P_{32}$, $P_{33}$ or a Fracture Count. $P_{10}$ is the most readily measured of the possible inputs, correlating to a borehole or scanline fracture count. Due to the directionality of the measurement, a $P_{10}$ value is associated with one or more FracMan well object(s), which can be thought of as boreholes or sample lines. Intervals along the length of the well object can also be used in FracMan to apply different intensity values to different zones, such as when the well crosses multiple geotechnical domains. If a $P_{10}$ value is used to define the fracture intensity in a DFN model, fractures are generated and the number of fracture intersections is checked against the selected well or well interval(s) until the specified $P_{10}$ value is reached. Fracture generation is halted when the first interval, all intervals, or the average of all intervals, as defined by the user, have reached the target $P_{10}$ value specified. It should be noted that if the $P_{10}$ reference well or well interval extends beyond the fracture generation volume, the full length of that interval is nonetheless considered to determine when the target $P_{10}$ has been reached. For example, if a 10 m long well with a target $P_{10}$ value of 1 fracture/m extends 5 m beyond the fracture generation volume, and the full well length is used to measure the $P_{10}$ value, this will create twice as many fractures in the generation region to compensate for the extent of the well that does not intersect any fractures. This is shown schematically in Figure 3-1, below.
Table 3-2: FracMan fracture intensity naming convention, based on slide 20 from http://fracman.golder.com/Gallery/guidtour.asp.

<table>
<thead>
<tr>
<th>Dimension of sampling region</th>
<th>Dimension of feature</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td>P_{00} (Length^{0})</td>
<td>Number of fractures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>P_{10} (Length^{-1})</td>
<td>Number of fractures per unit length of scanline (Frequency or linear intensity)</td>
<td>P_{11} (Length^{0})</td>
<td>Length of fracture intersections per unit length of scanline</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>P_{20} (Length^{-2})</td>
<td>Number of traces per unit area of sampling plane (Areal density)</td>
<td>P_{21} (Length^{-1})</td>
<td>Length of fracture traces per unit area of sampling plane (Areal intensity)</td>
<td>P_{22} (Length^{0})</td>
</tr>
<tr>
<td>3</td>
<td>P_{30} (Length^{-3})</td>
<td>Number of fractures per unit volume of rock mass (Volumetric density)</td>
<td>P_{31} (Length^{-2})</td>
<td>Area of fractures per unit volume of rockmass (Volumetric intensity)</td>
<td>P_{32} (Length^{-1})</td>
</tr>
</tbody>
</table>
Figure 3-1: Effect of reference well extending beyond fracture generation volume. (A) shows twice as many fractures as (B) for the same set definition, but different well length.

The $P_{32}$ (area of fractures per unit volume) value is a non-directional descriptor of fracture intensity; however, as this is nearly impossible to measure directly, it must be calculated from measured $P_{10}$ or $P_{21}$ values which are directional. Common practice is to estimate $P_{32}$ values for a rockmass based on the available measured data and the modeler’s experience and compare the resulting model $P_{10}$ values to those measured in the field. The $P_{32}$ estimate is adjusted until a good agreement is reached (Elmo, 2014, personal communication).

It should be noted that while a $P_{32}$ value is considered non-biased, it does not account for fracture size; a small number of large fractures may have the same area per volume as many small ones. Since the size of fractures plays a critical role in determining fracture connectedness, both the $P_{32}$ value and the fracture size should be reported to describe the topology of the fracture network.
3.1.4 Fracture Size

Fracture size is one of the most difficult parameters to measure and therefore to analyze to
determine an appropriate input for modeling. Further, fracture size plays a significant role in
determining block size and fracture connectivity.

Since fracture size cannot be measured directly in boreholes, practitioners must assume an
appropriate fracture size and distribution type if no mapping data is available for a particular site.
It is therefore useful to understand the effect of assumed fracture size on the total block size of the
synthesized rock mass.

In FracMan, the size is input as an equivalent radius; the area of the fracture is approximately the
same as that of a circle with the input equivalent radius, though other shapes may be specified.
To investigate the impact of fracture size on DFN models, several models of the same intensity,
but having different fracture sizes were run and compared using block size distribution curves.
Figure 3-2 shows an example of the variation in mean block size as well as total volume of blocks
formed for varying fracture sizes. The results shown below are based on fractures with a fracture
frequency (P_{10}) value of 1/m, and negative exponential size distributions. The fractures were 4
sided, equi-dimensional planes with equivalent radii of 1, 2, and 5 m, as shown. It is worth
noting that, as the input intensity was held constant for all models, the total area of fractures for
each model was approximately the same. However, the area was divided between many small
fractures, and fewer larger fractures as the size was varied. As it is often only possible to measure
intensity as a fracture count in a borehole, the impact of assuming a fracture size is relevant to
practical applications when data is limited or unavailable.
Figure 3-2: Block size distribution curves showing: a) variation in the mean block size, and b) variation in total volume of blocks formed for a P_{10} value of 1.

The curves in Figure 3-2 A are noteworthy because the model with the largest mean fracture size does not produce the largest mean block size, though it does produce the greatest total volume of blocks. This indicates that moderately sized fractures can make larger “staircase” blocks from fractures that intersect; while larger fractures can be considered continuous, producing blocks governed primarily by spacing.
3.1.4.1 Fracture Size Distribution Type

Many researchers have noted that recorded trace length distributions follow a log normal distribution; however, it has also been noted that several different underlying 3D distributions can produce a lognormal trace distribution due to sample bias. It is rarely, if ever, possible to verify the underlying distribution, thus it becomes necessary to make an assumption about the underlying distribution type.

There are eight different size distributions possible in FracMan:

- Negative exponential;
- Normal;
- Log Normal;
- Power Law;
- Gamma;
- Weibull;

To evaluate the effect of distribution type on block size, 9 models were run with 4 of the listed distribution types above: negative exponential, log normal, normal and power law.

The results from the block size analysis are shown in Figure 3-3 to Figure 3-5, below. Distributions showing mean block sizes as well as total volume of blocks formed are shown for each of the models.
Figure 3-3: Total volume of blocks formed and mean block size distributions for models with a mean fracture frequency of 1/m of varying fracture size distribution type.
Figure 3-4: Total volume of blocks formed and mean block size distributions for models with a mean fracture frequency of 2/m of varying fracture size distribution type.
Figure 3-5: Total volume of blocks formed and mean block size distributions for models with a mean fracture frequency of 5/m of varying fracture size distribution type.
The general trend observed in the above figures indicates that when fracture size is small, within approximately an order of magnitude of the mean spacing value, negative exponential distributions produce significantly larger blocks and more blocks in total. However, as fractures increase in size relative to the spaces between them, the effect of the distribution type becomes negligible.

Negative exponential distributions allow for large fractures to be generated that the other distributions examined do not; by definition, the standard deviation of a negative exponential is equal to the mean of the distribution. The other distribution types modeled here used a standard deviation equal to 25% of the mean. Though it would be possible to test the other distributions with standard deviations equivalent to their means, this was not considered typical of these distribution types. To illustrate how these compare, histograms showing the mean portion of fractures of each size, sorted by size distribution type are shown below in Figure 3-6 to Figure 3-8. It appears that a limited number of large fractures have a much greater impact on the overall blockiness of the rockmass than many very small fractures.

3.1.5 Fracture shape

The shape of the fracture surface in FracMan is defined by the number of sides and by elongation. As described in Chapter 2, fracture shape is not well understood. Evidence exists in the literature for both elliptical and polygonal fracture shapes. Typically, it is assumed that fractures that terminate in intact rock will be elliptical, while those that terminate on other fractures will be polygons, defined by the geometry of the surrounding fractures. As shown in Chapter 2, evidence indicates that fractures are likely to be elongated, reflective of the stress regime present in the rock at the time of fracturing; however measuring the orientation of the long axis and the ratio between the short and long axes may not be straightforward, if possible at all.
Figure 3-6: Histograms showing comparison of fracture sizes for different size distribution types with a mean radius of 1m.
Figure 3-7: Histograms showing comparison of fracture sizes for different size distribution types with a mean radius of 2m.
Figure 3-8: Histograms showing comparison of fracture sizes for different size distribution types with a mean radius of 5m.
Within FracMan, fractures are all assumed to be polygons, though the user may input the number of sides and the aspect ratio. The trend and plunge of the elongation axis is also user defined at the same time as the aspect ratio of the fracture. In this work, generated fractures have been assumed to be 4-sided with an aspect ratio of 1 (i.e. squares). While this may not be representative of typical fractures in nature, it provides a basic case for study. The reader is directed to Zhang et al. (2002) for methodology for determining elongation direction and ratios from mapping data.

### 3.1.6 Termination

In FracMan, termination refers to the percentage of a fracture set that terminates on other fractures. This is sometimes referred to as persistence elsewhere. Xs and Ts are used to describe the possible intersections, with the portion that end in Ts accounting for the termination percent of each set. When fractures are generated that intersect pre-existing fractures, FracMan checks the termination percentage to determine if a given fracture should be truncated; if so, the portion of the fracture extending past the intersection is thrown out. This results in a slightly skewed size distribution from that input by the user.

In this work, all fractures were assumed to have a termination of 0%; their size was not impacted by intersection with other fractures and all intersections would be X type intersections.

### 3.1.7 Block Size Algorithms

FracMan has three algorithms to calculate block size included in the code:

- SybilFrac, which uses a grid and counts grid cells contained within groups of intersecting fractures to determine the size of the block;
- Multi-Dimensional Spacing Calculation, which uses fracture frequency measured along 3 randomly located lines of user-defined orientation to calculate a statistical block size distribution based on the sampled spacing values; and
Ray Cast Calculations, which use points randomly located in the model space as a center for a specified number of rays to be extended until a fracture plane is intersected. For this work, the SybilFrac algorithm was used for all simulations as the other two options assume fractures are sufficiently continuous to form blocks in all cases. As SybilFrac uses a block counting methodology to define “stair blocks” within a grid system defined by the user, it is important that grid cells are adequately small to capture typical block sizes. The FracMan manual recommends that grid cells have a size of no more than 25% of the mean fracture spacing. The manual further suggests a maximum of 5 million cells per model – giving a recommended maximum model size of 150 blocks cubed to limit computing times.

3.2 Effect of modelling options on block size distributions in FracMan

3.2.1 Inclusion of bounding box in block size calculations
When carrying out a SybilFrac block size analysis, the user has the option to include the bounding box of the model in the block size distribution fractures or not. By selecting to include it, the full volume of the model will be made into “blocks”; however, the largest of these blocks may not be bounded by the fractures in the DFN, but rather the limits of the model. This is especially true when fractures are small compared to spacing, and the total volume of blocks bounded by fractures is a small fraction of the total model volume. Including the bounding box in these types of DFNs can result in block size distribution curves skewed by an order of magnitude or more compared to a distribution of blocks formed by generated fractures alone. As fractures become large compared to spacing, this effect becomes negligible and incorporating the model edges may be more convenient for some applications.

To illustrate this, several iterations of a range of models including and excluding the bounding box were run and block size distribution curves generated. Figure 3-9 shows the results from 5 iterations of five different models. It should be noted that these are comparisons of the mean of the same five realizations of fracture sets, thus the variation between the curves of the same
colour is due solely to the incorporation of the bounding box as no other variation exists.

Figure 3-9: Block size distribution curves with Fracture frequency (FF) and equivalent Radii (R) as labeled. The models not incorporating the bounding box are normalized to the total volume of blocks formed by fractures, while those including the bounding box are normalized to the model extents.

3.2.2 Minimum bounding box size to minimize edge effects

As with most numerical modeling, DFN models need to use model dimensions that minimize boundary effects. This may be evaluated in terms of the minimum size that captures the “true” behaviour of the rockmass in question for large-scale problems, or in terms of the scale of the problem, which may impact the relevant scale of the modeling. Though larger model space is generally better in terms of model accuracy, the computing power and time required is also increased, thus an optimization approach is required.

With respect to block size, it is found that for the same fracture network, the mean block size increases with increasing model volume, up to a point, and then becomes consistent. A model with sides between 15 and 20 times the mean fracture spacing and grid cells with sides of 1/100th of the model side appears to be adequate for the models tested. Figure 3-10 and Figure 3-11
below show the effect of adjusting the bounding box on block size distributions for models with mean spacing of 1m and 0.5 m, respectively.

![Graph showing block size distribution curves for models with different bounding box sizes.]

**Figure 3-10:** Mean block size distribution curves for a model with a Fracture frequency of 1/m and equivalent radius of 2m sampled at various model sizes.

![Graph showing block size distribution curves for a model with a fracture frequency of 2/m and equivalent radius of 2m sampled at various model sizes.]

**Figure 3-11:** Mean block size distribution curves for a model with a fracture frequency of 2/m and equivalent radius of 2m sampled at various model sizes.

3.2.3 Minimum number of realizations required

As FracMan is based on Monte Carlo simulations based on a range of data, multiple realizations of each model are required to give a range of outputs and to find a reasonable average value for
the model. No literature or documentation was found indicating standard practice or a recommended number of realizations; however it was assumed that 10 realizations would be adequate for most applications, and that less could potentially be acceptable as well. To test this, several models were run with 10 realizations; the mean and median values from all 10 realizations were compared to the mean and median from realizations 1 through 5 and those from 6 through 10. When the bounding box of the model was large enough, as described above, 5 realizations produced results approximately equal to those from 10 realizations; however, when the bounding box was small relative to the mean block size, the results were much more varied. It is worth noting that running additional realizations – up to 20, as shown in Figure 3-12, below, - with a too-small model, adds to the variability of the results. Thus, if the model is larger than about 15 times the mean spacing, as described above, 5 realizations appears to be adequate. From models considered in this work, when 5 realizations were examined, it was typically observed that 3 would produce similar results with an outlier on either side of the cluster; thus it is not recommended that fewer than 5 realizations be used as this provides confidence in where the true mean should lie. However, if the excavation is at a smaller scale than the suggested 15 times spacing limit, more of these smaller realizations should be run to determine the full range of possible outcomes. A stopping criterion is not investigated here; however it is suggested that further work be done to establish a more consistent method to evaluate when an adequate number of realizations have been run to provide representative results, particularly when models are smaller than the recommended 20 times the mean spacing. It is suggested that a minimum of 5 realizations is required and that an average of mean block sizes from each subsequent realization be used to determine when the full range of variability has been captured and further realizations are not required.

Figure 3-12 shows the mean and median values for each group of 5 realizations to compare if the mean or median would be more appropriate. The variation between these two values is much
greater when results are more variable (i.e. for smaller models), but becomes negligible as model results become more consistent.

3.3 Summary

The input parameters for geometric fracture network generation were discussed. The inputs that impact fracture network geometry were examined using block size distribution curves.

Figure 3-12: Variability of mean block size distribution curves for various model sizes.
It was found that models can be sensitive to fracture size when the fracture mean equivalent radius is within about an order of magnitude of the spacing value. For fractures that are large relative to spacing, results are consistent, and are not sensitive to assumed fracture size distribution type. Similarly, the incorporation of the block size analysis of the model boundary has a significant impact on models with wide spacing, but negligible effect on models with close spacing compared to fracture size.

For consistent block size analysis results, models should have extents 15 to 20 times larger than the mean spacing of the sets. This correlates to Sen and Kazi’s (1984) observation that true population values and scanline estimates of spacing become almost equal when the scanline length is 20/λ; though Priest and Hudson (1976) suggest a length of 50/λ to achieve acceptable results. The results for these models suggest agreement with Sen and Kazi. For smaller models, it was found that more realizations resulted in increased variability of results, and thus, whenever possible, it is preferable to run fewer realizations of larger models rather than many realizations of smaller ones.
Chapter 4

Using Discrete Fracture Networks to Evaluate Sampling Biases

4.1 Introduction

While many sampling biases are recognized, and some are accounted for, other aspects of fracture network geometry are more difficult to study and thus more difficult to analyze. One such parameter is fracture size. In this chapter, simple fracture networks created in FracMan to compare sampled data with the underlying network to evaluate the patterns and biases that emerge. Understanding of these patterns permit a modeler to better evaluate, and make more informed assumptions about the field data that is to provide the basis of this type of model, with particular focus on fracture size and intensity.

This chapter examines the limitations of 1D (borehole) and 2D (mapping) data and how sample size or data collection method may further affect the information collected. In addition, RQD values and their relationship to block sizes are examined. Outputs from simple FracMan models are compared to commonly accepted equations for estimating block size.

4.2 Orientation bias in boreholes – Fracture Frequency and RQD

4.2.1 Fracture Frequency

The frequency of fractures in a scanline or borehole survey is dependent on the angle between the scanline and the fractures being measured. Sampling lines perpendicular to the fracture set produce the highest fracture frequency value (Hudson and Priest, 1979). For two sets, the orientation of the maximum fracture frequency (from Hudson and Priest, 1979) can be measured as follows:

\[ \tan \theta = \frac{\lambda_2}{\lambda_1} \]  

(4-1)
Where θ is the angle between the sample line and the normal to both sets, and λ₁ and λ₂ are the fracture frequencies (number of fractures per unit length, measured normal to each set) for sets one and two, respectively.

The max value of the fracture frequency for two sets, according to Hudson and Priest, is equal to:

\[
\lambda_{\text{max}}^2 = \lambda_1^2 + 2\lambda_1\lambda_2\cos\phi + \lambda_2^2
\]  

(4-2)

Where \(\lambda_{\text{max}}\) is the maximum fracture frequency along a sampling line, and \(\lambda_1\) and \(\lambda_2\) are defined as above. The angle between the sets is described by \(\phi\). The reader is referred to Hudson and Priest (1979) for the derivation of this equation.

For more than two sets, assuming some knowledge of set orientation and spacing, the following relationship that accounts for the contribution of each set to the total fracture frequency along a given orientation, also from Hudson and Priest (1979), can be used:

\[
\lambda_\theta = \sum_{i=1}^{m} \lambda_i \cos\theta_i
\]  

(4-3)

where \(\lambda_\theta\) is the total fracture frequency along a scanline at a given angle, \(\lambda_i\) is the fracture frequency of the \(i\)th set, measured along the normal to the set and \(\theta_i\) is the acute angle between the scanline and the normal to the \(i\)th set. It is worth noting that this equation does not account for variations in fracture size.

To compare this equation with FracMan outputs, and to investigate the effect of non-continuous fractures on linear samples, models were set up with 3 orthogonal joint sets oriented at 090/85, 270/15 and 000/85 with intensities and fracture sizes as described in Table 4-1, below. Five realizations of each model were run. The models were sampled using a rosette of virtual boreholes to measure the resulting fracture frequency. The virtual boreholes were oriented with trends at 22.5° intervals, starting at 0°, and plunges of 45, 55, 65, and 75 degrees, creating 64 sample lines through the generated fracture networks.
Table 4-1: Mean spacing and fracture size for the sampled models. The mean P₃₂ of the sampled models is also given.

<table>
<thead>
<tr>
<th>Model</th>
<th>Input Mean spacing</th>
<th>Input Mean Radius</th>
<th>Mean P₃₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>1</td>
<td>2.95</td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>2</td>
<td>2.72</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>5</td>
<td>2.47</td>
</tr>
<tr>
<td>D</td>
<td>0.5</td>
<td>1</td>
<td>6.1</td>
</tr>
<tr>
<td>E</td>
<td>0.5</td>
<td>2</td>
<td>6.0</td>
</tr>
<tr>
<td>F</td>
<td>0.5</td>
<td>5</td>
<td>5.09</td>
</tr>
<tr>
<td>G</td>
<td>0.2</td>
<td>1</td>
<td>14.5</td>
</tr>
<tr>
<td>H</td>
<td>0.2</td>
<td>2</td>
<td>14.09</td>
</tr>
<tr>
<td>I</td>
<td>0.2</td>
<td>5</td>
<td>12.87</td>
</tr>
</tbody>
</table>

Figure 4-1 shows the boreholes in the model space.

Figure 4-1: Screen shot of virtual boreholes used to sample generated fracture networks. Boreholes of the same plunge have the same colour.

The expected frequencies for each borehole were calculated using equation 4-3 and the input frequencies from the DFN models. Only 3 diagrams are required for the 9 models, as the fracture size does not impact the expected frequency. These are displayed in radar plots next to the radar plots of the mean measured fracture frequency from the virtual boreholes of the nine negative exponential models in Figure 4-2 below.
Figure 4-2: Radar plots showing the mean measured fracture frequencies from 5 realizations of the models described in Table 4-1, above. The trend of each sample line is shown around the perimeter of the plot; the measured frequency increases outward from the center. Sample lines with the same plunge are grouped together in a set, coloured as shown.
The figure shows that the models with longer fractures produce results closest to the expected fracture frequencies; this is logical as the equations used to calculate expected fracture frequency assume continuous fractures. Additionally, as noted in Table 4-I, the $P_{32}$ values for the models with the smaller mean fracture size are slightly greater than those for the models with the largest fractures and the same $P_{10}$ value.

It is also noted that the boreholes inclined at 75° from horizontal exhibit less variation than the shallower boreholes and give fracture frequencies that are lower than the expected values. This is due to the orientations of the fracture sets in these models; the steep boreholes would rarely intersect the two sub-vertical sets, but would intersect the sub horizontal set at approximately the input frequency.

For the models which include the smallest mean fractures, a maximum variation of about 40% from the expected value is observed along the orientations of highest fracture frequency, while the lowest difference in measured frequency is up to 10% less than the expected value. The peaks in fracture frequency are observed at the midpoint between the sub vertical sets, where fracture frequency should be highest according to Equation 4-3. While Priest (1993) showed abrupt changes in fracture frequency diagrams when sampling planes paralleled a fracture set strike and thus produced a low fracture frequency, the same was not expected along the orientations with the highest expected values.

It is presumed that this discrepancy is in part due to the distribution type and the model intensity measurement; the negative exponential distribution creates large numbers of very small fractures but fewer large fractures, and model generation was controlled by the fracture count along a borehole perpendicular to the set. As a result, when sampling at a moderate angle to more than one set, many small fractures could be intersected by the synthetic boreholes. When fractures
were larger, fewer total fractures were generated to achieve the same fracture frequency in the control borehole, thus fewer fractures existed for sampling boreholes to intersect.

The deviation of the measured fracture frequency from the expected values from several boreholes could be used to infer the approximate fracture size if fractures are short, or could give a greater degree of confidence in assuming longer fractures where less variation is present. However, this would only be possible if there was a high degree of confidence in a negative exponential fracture size distribution, or if it could be shown that other distribution types followed a similar pattern.

To evaluate this, the same sampling process was repeated for fractures with other types of size distributions to determine if the relationships observed in Figure 4-2 apply. The input variables for each set are the same as those described above, but using normal, lognormal and power law size distributions. The deviation of the fracture size for each of the normal and lognormal model types is set at 25% of the mean. The power law distribution is governed by minimum value and an exponent. These were selected to give comparable mean and standard deviation values to the normal and lognormal distributions using the following equations (from the FracMan user’s manual):

\[
\bar{x} = \left(\frac{b-1}{b-2}\right) x_{min} \text{ for } b > 2
\]

\[
x_{\sigma} = \left(\frac{b-1}{b-3}\right)^{1/2} \left(\frac{x_{min}}{b-2}\right)
\]

\[
x_{min} = \left(\frac{b-2}{b-1}\right) \bar{x}
\]

Where \(\bar{x}\) is the mean value, \(x_{\sigma}\) is the standard deviation, \(x_{min}\) is the power law minimum value and \(b\) is the exponent. The exponent was 6.12 for all models.

The exponential distribution type used above has, by definition, a standard deviation equal to the mean. The distributions of the fractures generated for each model sampled are shown in Chapter 3.
The expected values calculated from Equation 4-3 are also shown on these figures for comparison. These are the same 3 plots as those shown above as the fracture size distribution is not incorporated in the estimate.

The measured fracture frequencies of the normal, lognormal and power law distribution models show much less variation than those measured in the negative exponential distribution model. The measured frequencies are also in much better agreement with the expected frequencies. The abrupt peaks observed in the 45 and 55 degree plunging sample lines seen in Figure 4-2 are not present in the other model types. The discrepancy may be due to the presence of a much larger number of small fractures in the negative exponential distribution; the small fractures are unlikely to intersect the control borehole or impact the P_{32} value significantly, but due to their very large numbers, will impact the fracture count in the sample lines along the peak orientations. This is further evidenced in Figure 4-2, where the models with the shortest mean fracture radii show the greatest deviation from the expected values.

The following plots indicate that while theoretically it might be possible to approximate fracture size by correlating fracture frequencies in boreholes of varying orientations in the same region, this would only be valid if the fracture sizes followed an exponential distribution. This assumption is very difficult to test and is complicated by the sampling biases affecting the data that would be used for verification (Mauldon, 1998). Further, the deviation is unlikely to be distinguishable from natural variation encountered in a rockmass. As there is no way to verify typical fracture size distributions in 3D, it is unreasonable to infer fracture size from variation in fracture frequency. As described in Chapter 2, it may be possible to use other indirect indicators, such as fracture aperture, to estimate mean fracture sizes when only boreholes are available.
Figure 4-3: Fracture frequency radar plots for models using a normal fracture size distribution.
Figure 4-4: Fracture frequency radar plots for models using a lognormal fracture size distribution
Figure 4-5: Fracture frequency radar plots for models using a power law fracture size distribution
4.2.2 RQD

As discussed in Chapter 2, the RQD value is linked closely with fracture frequency, and subject to similar orientation biases. An expected RQD value based on total fracture frequency was proposed by Priest and Hudson (1976) assuming a negative exponential distribution of fracture spacings:

$$RQD = e^{-\lambda t} \left( -\lambda t - 1 \right)$$  \hspace{1cm} (4-7)

Where $\lambda$ is the fracture frequency and $t$ is the threshold value, typically taken as 0.1 m. Priest and Hudson then used the above equation to demonstrate that rockmasses with a mean spacing of 0.3 m or greater would give RQD values of 95% or more.

The virtual boreholes from the models described above were used to sample RQD values as well, to compare the results to fracture frequency. For the models described above with a $P_{10}$ of 1 or 2, all fracture size distribution types produced RQD values over 94%. Overall, orientation bias is less pronounced in RQD values than in fracture frequency measurements; the 0.1 m threshold value acts as a buffer to reduce orientation bias compared to fracture frequency values alone.

These results indicate that within the range of RQD sensitivity, specifically, where mean spacing is less than 0.3 m, the RQD value is more representative of the rockmass than fracture frequency. For wider spacings, where RQD is insensitive, a fracture frequency value or $RQD^*$, from Priest and Hudson (1976) and described in Chapter 2, with a project-appropriate threshold value, may be a more useful parameter, particularly for larger excavations.

4.2.2.1 RQD and Block Size distributions

In addition to the above models, smaller DFN models with closer spacing values were also created to compare RQD values with calculated block size distributions. The model parameters are shown below in Table 4-2. All models used an exponential fracture size distribution.
Table 4-2: Parameters for models used to evaluate RQD measurements.

<table>
<thead>
<tr>
<th>Model</th>
<th>( P_{10} )</th>
<th>Mean spacing</th>
<th>Mean Radius</th>
<th>Mean ( P_{32} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>J</td>
<td>5.5</td>
<td>0.18</td>
<td>1</td>
<td>16.867</td>
</tr>
<tr>
<td>K</td>
<td>6.6</td>
<td>0.15</td>
<td>1</td>
<td>20.595</td>
</tr>
<tr>
<td>L</td>
<td>7.9</td>
<td>0.13</td>
<td>1</td>
<td>24.695</td>
</tr>
<tr>
<td>M</td>
<td>13.8</td>
<td>0.07</td>
<td>1</td>
<td>42.214</td>
</tr>
<tr>
<td>N</td>
<td>18.6</td>
<td>0.05</td>
<td>1</td>
<td>56.600</td>
</tr>
<tr>
<td>O</td>
<td>27</td>
<td>0.04</td>
<td>1</td>
<td>84.112</td>
</tr>
</tbody>
</table>

The fracture networks created in these models were then clipped to a 5 m cube sample size and block size analysis was completed on 5 iterations of each model. As the fracture frequencies are higher than the models discussed above, the expected RQD values are more sensitive for these models. The block size distribution curves and the associated \( P_{10} \) values at a variety of sampling orientations are shown in Figure 4-6 below. The measured RQD values for the same models are also shown with the block size distribution curves in Figure 4-7. While the RQD and \( P_{10} \) values are approximately the inverse of one another, the RQD values display less variation than the \( P_{10} \) values for different orientations. This becomes more pronounced as the rock becomes less fractured, and RQD remains high.

The irregular shape seen in the curves is due to the block computation algorithm that uses grid cells to approximate block volumes, thus all volumes are a multiple of a single grid cell. When grid cells are close to the same size as the blocks being formed, there are concentrations that form steps in the block size distribution curves. As blocks become larger relative to the grid cells, this effect is not discernible.

These figures show that for the same fracture network, a range of RQD and fracture frequency values are possible, depending on the direction of sampling, and that these correspond to a range of block sizes. It is also observed that a greater range of fracture frequency values exists for a given rockmass while the RQD range is narrower.
Figure 4-6: Block Size distribution and fracture frequency plots
Figure 4-7: Block size distributions and RQD value radar plots
4.2.3 Converting linear sampling to a 3D intensity

The $P_{32}$ value for a fracture network provides a description of fracture intensity that is free of directional bias. However, as there is no way of measuring $P_{32}$ directly, it must be estimated from borehole or mapping data, which is subject to orientation bias. Some modelers will select several $P_{32}$ values and compare the resulting $P_{10}$ values from synthetic sample lines to those recorded from boreholes or scanlines in the field to determine an appropriate $P_{32}$ value.

FracMan uses the following equations from Wang (2005) to estimate $P_{32}$ values from $P_{10}$ values:

$$P_{10} = P_{32} \int_{0}^{\pi} |\cos \alpha| f_{A}(\alpha) d\alpha$$  (4-8)

Where $\alpha$ is the angle between the sampling line and the fracture normal and $f_{A}(\alpha)$ is the probability density function of $\alpha$.

The equation assumes that the fracture orientations follow a Fisher Distribution and that the fractures are constant size or unbounded. The models examined here had a constant orientation distribution and one of four different size distributions. The intensity in the models was controlled by a target $P_{10}$ value; fracture generation stopped when a specified well reached the input $P_{10}$. The constant orientation means that Equation (4-5) is equal to one when considering a well normal to the set. As wells normal to each set were used as the specified $P_{10}$ control, the input intensity for each set could be added to give the expected $P_{32}$. Deviation from this value is likely due to fracture size variation, which is not in accord with the assumption that all fractures are constant size or unbounded.

The results for the four distribution types for the nine models described in Table 4-1 are shown below. Overall, the measured values typically fall within 10% of the predicted values, and those that do not are highlighted. However, the negative exponential models with the largest (5 m mean radius) fractures all have more than a 10% deviation from expected value indicating that as very large fractures are more likely to intersect a borehole, fewer of them are required to produce an equivalent $P_{10}$ value.
Table 4-3: Comparison of measured and predicted $P_{32}$ values

<table>
<thead>
<tr>
<th>Model (from Table 4-1)</th>
<th>$P_{10}$</th>
<th>Mean Radius</th>
<th>Negative Exponential</th>
<th>Lognormal</th>
<th>Normal</th>
<th>Power Law</th>
<th>Predicted from eq’n (4-8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>1</td>
<td>2.95</td>
<td>3.049</td>
<td>2.950</td>
<td>2.830</td>
<td>3</td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>2</td>
<td>2.717</td>
<td>3.024</td>
<td>2.950</td>
<td>3.010</td>
<td>3</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>5</td>
<td>2.470</td>
<td>2.900</td>
<td>2.880</td>
<td>2.790</td>
<td>3</td>
</tr>
<tr>
<td>D</td>
<td>2</td>
<td>1</td>
<td>6.102</td>
<td>6.197</td>
<td>5.850</td>
<td>5.988</td>
<td>6</td>
</tr>
<tr>
<td>E</td>
<td>2</td>
<td>2</td>
<td>6.000</td>
<td>6.022</td>
<td>6.139</td>
<td>6.034</td>
<td>6</td>
</tr>
<tr>
<td>F</td>
<td>2</td>
<td>5</td>
<td>5.090</td>
<td>5.880</td>
<td>5.860</td>
<td>5.746</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
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<td>1</td>
<td>14.498</td>
<td>15.505</td>
<td>15.320</td>
<td>16.451</td>
<td>15</td>
</tr>
<tr>
<td>H</td>
<td>5</td>
<td>2</td>
<td>14.086</td>
<td>15.185</td>
<td>14.928</td>
<td>15.374</td>
<td>15</td>
</tr>
<tr>
<td>I</td>
<td>5</td>
<td>5</td>
<td>12.867</td>
<td>15.164</td>
<td>15.180</td>
<td>15.720</td>
<td>15</td>
</tr>
</tbody>
</table>

As the negative exponential distribution inherently has a large standard deviation, and, as was shown in the fracture size distribution histograms in Chapter 3, more large fractures than the other model types that were assigned a smaller standard deviation. This pattern is also seen to a lesser extent in the lognormal distribution models. For the normal and power law distributions, it is more difficult to discern a pattern. It is worth noting, however, that these distribution types preclude smaller fractures from being generated, especially for the models with the largest mean fracture size. Because a large fracture can only intersect the control borehole once, it is possible to have a higher $P_{10}$ value for the same or smaller $P_{32}$ value if many small fractures are accounting for the increased fracture frequency.

4.3 Comparison of 2D trace length distributions to 3D Fracture radius distributions

Based on the assumption of fractures as circular discs, Warburton (1980) used the work of Wicksell (1925, 1926) to derive the following equation describing the probability density distributions of trace lengths over a sample plane:
\[ f(l) = \frac{l d l}{\mu_s} \int_l^\infty \frac{c(s) d s}{\sqrt{s^2 - l^2}} \quad (l \leq s) \]  

(4-9)

Where \( l \) is the length of the trace, \( s \) is the diameter of the disc, \( \mu_s \) is the mean diameter of the fractures and \( c(s) \) is the distribution of the discontinuity diameters. It is derived from the assumption that for any discontinuity of diameter \( s \), to intersect the sampling plane, the center of that discontinuity must lie within a distance of \( s/2 \) of the sampling plane. By summing the probabilities we can derive an expected trace value. However, as underlying size distributions are seldom, if ever, known, an approach more suitable for application to field data is required.

The above equation incorporates the calculation for determining the length of a chord of a circle located some distance \( d \) from the center of the circle:

\[
\text{chord length} = 2\sqrt{r^2 - d^2}
\]  

(4-10)

A circle of radius 1 was assumed and the resulting equation was plotted, as shown in Figure 4-8, below.

![Figure 4-8: Plot of chord length for a given distance from the center of a circle](image-url)
The above plot can be used for any circle size by multiplying the values on the axes by the radius of that circle. The curve also represents a cumulative distribution curve, showing the probability that a trace is longer than a given distance. For instance, at the midway point along the radius, the trace length is $1.73r$; meaning that there is a 50% chance that a given trace is longer than this assuming a constant fracture size distribution and a random distribution of fractures in space. There is only a 15% chance that a trace will be shorter than the radius.

To show this, a DFN model was constructed in FracMan using fractures with the maximum number of sides allowed in FracMan, all having a radius of 2m. Three sets with constant orientations of 090/85, 270/15 and 000/85 were implemented in the model. This model was sampled using 48 different sampling planes, each a 35 m square, with strikes at 45 degree intervals and dips in 15 degree intervals. The sampling planes are shown in Figure 4-9, below.

![Image of traceplanes](image)

**Figure 4-9: Screen capture of traceplanes used to sample FracMan models.**

The resultant trace length distribution curve, for traces from all planes, was plotted in FracMan and is shown in Figure 4-10, below.
Figure 4-10: Cumulative distribution

The above figure follows a similar pattern to the chord length plot, though the match is not perfect. The measured trace lengths show that about 25% of the sample population consists of traces shorter than the input radius. The median trace length is about 1.6 times the radius. Overall, the sampled traces are skewed about 10% shorter than those predicted by the chord length curve. The discrepancy illustrates the effect of truncation along sample plane or model edges. It is important to recognize this behavior both when using information from a DFN and when interpreting field trace length data.

Further model realizations were run using a smaller generation volume and without clipping the fractures to remove this discrepancy. The resulting cumulative distribution curve matches the predicted values from the chord length plot very closely. The plot is shown below, in Figure 4-11.
The above example considers only circular fractures of the same size; in a more typical rockmass, fractures of various sizes and shapes may be present, but will not be sampled at the same rate. From Equation (4-9) it can be inferred that traces are formed only when the center of a circular fracture is located one radius or less from the sample plane; thus smaller fractures are statistically less likely to intersect the sampling plane, even when there are more small fractures. For elliptical or polygonal fractures, similar logic applies, but further calculations are required to account for geometry and orientation bias.

The above plots show the importance of considering the size of the sample window when determining appropriate inputs for fracture size and adjusting values for truncation limits.

### 4.4 Comparison of trace lengths, sampled radii and 3D fracture networks

It has been noted by several researchers (Hudson and Priest, 1979; Baecher, 1983) that the trace size distribution may or may not follow the same size distribution as the underlying 3D network.
Most notably, it has been shown that both negative exponential and lognormal 3D distributions produce lognormal trace distributions and traces are most commonly found to follow a lognormal trace distribution.

The models described in Table 4-1 were sampled using the surfaces shown in Figure 4-9. FracMan allows the portion of the underlying fracture network intersected by the traceplanes to be evaluated, and provides details on the traces resulting from these intersections. This allows a comparison between the measured trace sizes, the size of the fractures that were intersected and the entire underlying 3D network being sampled. The histograms shown in Figure 4-12 to Figure 4-15 below illustrate this comparison for the models with a $P_{10}$ of 1. The same trend is observed with a proportional increase in the value of the y axis for the models with $P_{10}$ of 2 and 5 but these are not shown here for the sake of brevity.

The mean equivalent radius and equivalent diameter for the total 3D network and the portion of the 3D network that intersects the sample plane are shown with the resulting trace length distributions. It should be noted that a fracture intersecting more than one of the sampling planes is counted at each intersection, thus the sampled network may have more fractures than the underlying 3D network, particularly when examining the largest fractures. While this effect is exaggerated by the close proximity of the sample planes in the model space, it is analogous to mapping a fracture that extends through several mapping windows, such as multiple benches, and is logged separately each time the fracture is crossed.

It should also be noted that these trace length distributions account for all traces intersected; in practice, fractures below some cutoff threshold, determined either by the project needs or by what the mapper considers practical, would not be included.

The mean equivalent radii of the fracture network, and the fractures sampled are shown along with the mean trace length for each of the models in Table 4-4 below.
Figure 4-12: Comparison of the equivalent radii distribution in 3D to the portion of that network sampled by the traceplanes shown in Figure 4-9 to the trace lengths resulting from those intersections for a negative exponential size distribution.
Figure 4-13: Comparison of the equivalent radii distribution in 3D to the portion of that network sampled by the traceplanes shown in Figure 4-9 to the trace lengths resulting from those intersections for a lognormal size distribution.
Figure 4-14: Comparison of the equivalent radii distribution in 3D to the portion of that network sampled by the traceplanes shown in Figure 4-9 to the trace lengths resulting from those intersections for a normal size distribution.
Figure 4-15: Comparison of the equivalent radii distribution in 3D to the portion of that network sampled by the traceplanes shown in Figure 4-9 to the trace lengths resulting from those intersections for a power law size distribution.
Table 4-4: Mean equivalent radii and trace lengths for a variety of models.

<table>
<thead>
<tr>
<th>Model</th>
<th>P&lt;sub&gt;10&lt;/sub&gt;</th>
<th>Mean R</th>
<th>Negative Exponential</th>
<th>Lognormal</th>
<th>Normal</th>
<th>Power Law</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3D</td>
<td>2D</td>
<td>trace</td>
<td>3D</td>
<td>2D</td>
<td>Trace</td>
</tr>
<tr>
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<td>4.42</td>
<td>11.52</td>
<td>10.03</td>
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</tbody>
</table>

The above values were normalized to show the relationship between mean fracture sizes for the 3 domains considered here.
Table 4-5: ratio between Equivalent Radii and trace lengths for each of the models tested.

<table>
<thead>
<tr>
<th>Model</th>
<th>P₁₀</th>
<th>Mean R</th>
<th>2d/3d</th>
<th>Trace/2d</th>
<th>Trace/3d</th>
<th>2d/3d</th>
<th>Trace/2d</th>
<th>Trace/3d</th>
<th>2d/3d</th>
<th>Trace/2d</th>
<th>Trace/3d</th>
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</tr>
</thead>
<tbody>
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<td>1</td>
<td>2.82</td>
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<td>1.10</td>
<td>1.38</td>
<td>1.52</td>
<td>1.09</td>
<td>1.47</td>
<td>1.60</td>
<td>1.13</td>
<td>1.40</td>
<td>1.58</td>
</tr>
<tr>
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<td>1</td>
<td>2</td>
<td>2.18</td>
<td>1.17</td>
<td>2.55</td>
<td>1.10</td>
<td>1.31</td>
<td>1.43</td>
<td>1.14</td>
<td>1.32</td>
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<td>1.27</td>
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<td>1.12</td>
<td>1.38</td>
<td>1.55</td>
<td>1.11</td>
<td>1.40</td>
<td>1.55</td>
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<td>1.60</td>
<td>1.14</td>
<td>1.40</td>
<td>1.59</td>
<td>1.14</td>
<td>1.38</td>
<td>1.57</td>
</tr>
<tr>
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<td>1.14</td>
<td>3.03</td>
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<td>1.58</td>
<td>1.16</td>
<td>1.33</td>
<td>1.54</td>
<td>1.22</td>
<td>1.31</td>
<td>1.60</td>
</tr>
<tr>
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<td>2.27</td>
<td>1.29</td>
<td>1.14</td>
<td>1.47</td>
<td>1.29</td>
<td>1.16</td>
<td>1.50</td>
<td>1.27</td>
<td>1.14</td>
<td>1.45</td>
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</tbody>
</table>
The histograms show that the sampled portion of the network (2D equivalent radii) increases as the mean fracture size increases. Large fractures are sampled more often than they actually occur, while small fractures are barely sampled at all. The difference is very apparent for the negative exponential distribution which has significantly more small fractures compared to the other distribution types considered. Even the largest mean equivalent radius considered shows a far greater number of small fractures in the underlying 3D network than what is sampled. For the other model types, however, the portion of the underlying network sampled in 2D increases as the mean equivalent radius increases. As the lognormal, normal and power law distributions prevent smaller fractures from being generated when the mean equivalent radius is increased, the probability of sampling the larger fractures increases and thus the sampled network contains more fractures than the underlying network. The under-sampling of small fractures and proportionately over-sampling of large fractures suggests that field data is likely to overestimate fracture size.

However, Table 4-3 shows that, for the negative exponential distribution models with 5 m mean equivalent radii, the mean trace length is shorter than the mean equivalent radius for the model, as a result of truncation. The ratio of mean trace length to 3D mean radius for the 5m negative exponential models is only slightly less than the ratios observed in the other negative exponential models. The remaining distributions produce a relatively consistent relationship between the mean trace length and the mean 3D equivalent radius for all models examined, with the ratio typically falling between 1.3 and 1.6. While this differs significantly from the negative exponential distribution, the discrepancy may be attributed to more oversampling of the large fractures on multiple closely spaced sampling planes.

Additional modelling using more widely spaced fracture planes or using randomly oriented fractures and a single sampling plane could be done to see the relationship of the negative exponential model to the generated trace lengths when no over-sampling occurs.
4.4.1 Inferring 3D intensity from 2D intensity

A relationship between \( P_{32} \) and the total trace length in an area was also developed by Wang (2005). The relationship is as follows:

\[
P_{21} = P_{32} \int_0^\pi \sin \beta f_B(\beta) d\beta
\]  

Where \( \beta \) is the angle between the mapping plane normal and the fracture plane normal and \( f_B(\beta) \) is the probability distribution of \( \beta \). Calculating the theoretical \( P_{32} \) value from \( P_{21} \) measurements is more difficult than calculating the \( P_{10} \) value in the theoretical example as each sampling plane would have to be examined individually and the number of fractures of each set counted and measured. Further, in practice, the \( P_{21} \) is subject to a size bias where small fractures are not measured and therefore not included in the total. The \( P_{21} \) value is not an allowed intensity input in FracMan, potentially due to the greater degree of bias inherent in its measurement. Dershowitz et al. (2000) illustrate this well, providing intensity data from the same section of access tunnel at Äspö, Sweden, mapped by different mappers focused on different scales. The coarser data gave a \( P_{21} \) value that was half of the more detailed measurements, indicating significant subjectivity and variability that would be difficult to compensate for directly.

4.5 Effect of sampling windows on trace length distributions

As described in Chapter 2, several methods have been developed that use the number of fracture terminations within a sample window of known area to estimate a mean trace length. The circular window method suggested by Zhang and Einstein (1998) and modified to incorporate fracture intensity and density by Rohrbaugh et al. (2002) appears to be the most reliable, provided an adequately sized circular window can be delineated and accessed. However, it is recognized that access for geological mapping purposes is frequently limited by short construction schedules, and high, vertical or sub-vertical faces that require special access equipment to map. Thus the limitations created by practical considerations should also be understood. Orientation bias is well understood and several methods exist to weight data accordingly.
To accurately represent a rockmass, the model limits must extend far enough to capture characteristic structures and behaviours; however, knowing what these are is dependent on the chosen input parameters. Thus, when collecting data about a rockmass, the sampling window(s) need to be large enough to include characteristic structures. Zhang and Einstein (1998) examined the effect of increasingly large sampling windows on the accuracy of the predicted results and indicate that the size of the sample window does not impact the mean trace length assessment when using their proposed sampling methodology. However, their data do indicate less variability between iterations with increasing sample window size and are dependent on a circular mapping window with the additional termination data collected. As bench or strip mapping is frequently not undertaken in this fashion, it is useful to determine the effect of more typical mapping practices on the collected data and subsequent modelling.

In practice, sampling windows are limited and biased by outcrop size, orientation and accessibility. Large exposures of rock are sometimes visible, but detailed mapping may require specialized access equipment. On a vertical or sub-vertical face, detailed geotechnical mapping is often limited by the height of the mapper. Though it is possible to approximate properties for some larger fractures from a distance, shorter discontinuities will likely not be included.

### 4.5.1 Varying Sampling Windows in a Simulated Rockmass

To assess the effect of sampling window size on measured average trace length, four of the models described in Table 4-1 were used. The models selected were B, C, E and F.

For each of the four models, square surfaces with side lengths of 8 m, 12 m, 16 m, 20 m and 64 m (for the 2m equivalent radii models) or 100 m (for the 5 m equivalent radii models) were used to compare average trace lengths. For each of the four models, 5 equi-probable fracture network realizations were created. For each surface size, 3 horizontal planes and 3 vertical planes were used and trace lengths were recorded for all traces resulting where fracture planes intersect the
square traceplane surfaces. Figure 4-16 shows a realization of each model at the 20 m scale. Figure 4-17 shows an example of the trace plane surfaces at the 20 m scale.

Figure 4-16: Example of model realizations at the 20m scale. Labels shown reference models described in Table 4-1.

Figure 4-17: Trace planes at the 20 m scale
Figure 4-18 shows examples of these trace planes at different scales. The trace planes are taken from the same realization of each model and are centered on the same point; thus the fractures on the 8m plane will be contained within the larger planes for that model.

Figure 4-18: Examples of traceplanes at, from left to right, 20 m, 16 m, 12 m, and 8 m. Models are labeled according to the labels in Table 4-1.

The average trace length for each category was computed as an arithmetic mean and the median by fracture number of the data set. Figure 4-19 shows that as the sample area is increased the mean trace length is also increased.
Figure 4-19: Mean trace lengths from mapping windows of various sizes for Model B.

The same process was followed for model F. It should be noted that the largest traceplane for this model had a side length of 100m, while the largest above was only 64. The results of this are shown in Figure 4-20.

Figure 4-20: Mean trace lengths from mapping windows of various sizes for Model C.

Though the smaller mapping windows give mean and median values that do approximate the expected average trace length, the largest windows indicate a much larger average than what was input. This anomaly is likely due to an over representation of the largest fractures that are counted for each intersection with each sampling surface.

It is expected that the mean trace length would increase as longer traces can be formed in larger windows; however, the measured mean increases beyond the input mean value. The reason for
this is two-fold: the small fractures that have been generated are not sampled and the large fractures are sampled more than once due to the proximity of the trace planes. Both of these factors skew the measured mean value larger than the underlying mean size.

4.6 A sample case
To compare the above investigation to more realistic data, a LiDAR scan of a rock cut located near Sutton, Quebec was used. An image of the scan is shown in Figure 4-21. From the scan, two smaller areas on either end of the rock cut were analyzed in detail. The relative positions of these areas are also shown in Figure 4-21. The software PlaneDetect (Lato and Vöge, 2012) was used to create a mask of the scanned cut and to identify surfaces with an area greater than 0.1m. Planes with similar orientations were grouped together in sets and relevant information was collected within each of the sets. A stereonet of all the surfaces identified in the scanned regions of interest was used to identify three sets and an average orientation for each. It should be noted that PlaneDetect locates surfaces, not fracture traces. Though more discontinuities may be visually identified, they were not included in the orientation data.

Figure 4-21: Image of LiDAR scan of rock cut near Sutton, Quebec. The green, blue and yellow shaded zones represent areas that have been selected for more detailed analysis. Only the zones on either end, labelled Section 1 and 2, are considered in this work.
In each of the two sections, smaller mapping windows were used to simulate typical windows that would be available – a 2 m high window, similar to what a mapper would be able to access in normal conditions, a 4 m window, similar to a mine adit or tunnel wall, and the full scan height of about 9 m, similar to a small mine bench or exposed road cut. The windows were the full width of the detailed areas; about 5 m and 8 m across for Section 1 and Section 2, respectively. The areas of interest are shown in Figure 4-22. These figures show the fractures that were considered, sorted by set, for each area. The 2 m and 4 m windows that were used are bounded by dotted and dashed lines, respectively.

The full size of any identified fracture intersecting the smaller windows was measured, regardless of whether it was fully contained within the window or not. These data were then grouped by set and by mapping window and plotted as histograms. The histograms are shown below in Figure 4-23. It should be noted that the data from the larger windows contains the data from the smaller windows.

Figure 4-22: Sections 1(left) and 2 (right) with identified discontinuity surfaces coloured by set; Set 1 in red, Set 2 in blue and Set 3 in green. The 2 m and 4 m sampling windows are also shown.
The histograms in Figure 4-23, show that the size of the mapping window has more impact on the more widely spaced sets. In Section 1, Set 2 would be difficult to interpret with the limited data, and Set 3 is not represented at all. It also appears that these distributions are bimodal, with a peak between 0.4 m and 0.6 m and another peak, at least relative to a lognormal distribution, between 3 m and 5 m. This captures what is seen on the rock cut scan; an overall smaller-scale fabric cut by larger fractures in places.

**Figure 4-23:** Histograms of the three identified fracture sets in both detailed areas at different sampling scales. The data from the larger windows contains the data from the smaller windows.
4.7 Block size distributions

Mean fracture sizes were inferred from the histograms shown in Figure 4-23 and used as input for a DFN model. Synthetic scanlines were used to develop fracture frequency values for input into FracMan. Realizations for each section were created based on these orientation, size and frequency data.

Block size distributions were computed for each section at the 10 m and 20 m model volume size. Though there was significant variation between realizations at both scales, the average block size distributions were very similar. This again seems to represent the scanned rockmass, where there are localized blockier zones, or a few large blocks that can skew a block size distribution, and other more massive regions with discontinuous and/or non-interconnecting fractures. The block size distribution curves are shown in Figure 4-24. Figure 4-25 provides a visual representation of the block size analyses for each of the two regions.

![Block size distribution curve](image)

**Figure 4-24:** Average block size distribution for 5 realizations at the 10 m and 20 m bounding box size.
Figure 4-25: Examples of block size analyses for a) Region 1 and b) Region 2.

Traceplanes, 10m by 10m, cut through the realizations at approximately the same orientation as the road cut were compared to the scan. An example of trace length data and the corresponding trace planes are shown in Figure 4-26 and Figure 4-27. The trace length distributions are similar to those measured on the LiDAR scan, however, the traces themselves do not resemble the patterns seen on the rock face. This may be because the actual scanned surface is not truly planar, but instead follows many natural discontinuity surfaces. The larger discontinuities also create local zones of instability, where the smaller blocks that might form in a model have already failed from the actual rock face. This may also be an example of models that match the measured data, but do not appear to reproduce the insitu conditions.

Figure 4-26: Region 1
This chapter has used DFNs to explore sample biases due to 1D and 2D sampling. In boreholes, it was shown that a negative exponential fracture size distribution can result in $P_{10}$ values that are up to 60% larger than the expected values, along some sampling orientations, based on the mean spacing of fracture sets. This is assumed to be as a result of the large number of very small fractures that are generated for this distribution type. A similar relationship was not found for other distributions that had fewer very small fractures.

It was also shown that while RQD is subject to orientation bias, it is less sensitive to orientation than the fracture count for the interval where RQD is appropriate (where mean fracture spacing is 0.3 m or less). For fracture networks with very wide spacings, RQD may not be a meaningful measurement.

FracMan was used to show the relationship between $P_{10}$ and $P_{32}$ for a range of models with different fracture size distribution types. Most of the models produced results in good agreement with the $P_{32}$ estimated from input parameters, despite differing model types that were assumed in the approximation equation.
The mean fracture radii for a range of generated networks were compared to the mean radii of the fractures that intersected a series of sampling planes and to the traces formed as a result of those intersections. It was found that as the mean fracture size increased, the total portion of fractures sampled also increased. This effect was emphasized by clustered sampling planes that allowed a single fracture to be counted for every intersection with a traceplane. This was combined with an undersampling of very small fractures that failed to intersect the sampling planes at all. The resulting ratio between mean measured trace length and the underlying mean 3D equivalent radius was between about 1.3 and 1.6 for all model types tested except the negative exponential. Due to the increased number of very large fractures that intersected many sample planes, the ratio was much higher; however, truncation of fractures may serve to reduce this discrepancy somewhat.

A Lidar scan of a rock face was used to compare the effect of sampling windows of different sizes on measured trace length distributions and subsequent modelling. The models generated matched the sample data reasonable well, but did not appear to fully capture what is visually observed in the rock face. This illustrates the importance of calibrating and comparing DFN models not only to the input data used to build them, but also to the in situ rockmass, whenever possible.
Chapter 5

Using block sizes for rockmass classification

This Chapter relies heavily on work presented in the paper “Blockiness as a Rockmass classification tool” by Palleske et al. prepared for ARMA 2014.

5.1 Introduction to blockiness

Within this work, the term blockiness refers to the size distribution of blocks formed by a rockmass as well as the percentage of the rock mass that is completely bounded by fractures. It is assumed that in some cases, zones of unfractured rock extend beyond the scale of a particular excavation and that these zones may be considered intact. As the scale of an excavation decreases, relative to the block size, very large blocks become “intact” rock, if the block is larger than the excavation under consideration. This is shown schematically in Figure 5-1, which shows the same model realization sampled at different scales, and the resulting blocks generated from those fractures. The blocks in the lower portion of Figure 5-1 are coloured by volume, with cool colours for small blocks and warm colours for blocks of larger volume.

As described in Chapter 3, the mean block size increases as the total volume of rock simulated is increased, up to a threshold value, as a larger model volume permits the formation of larger blocks. Above a certain (critical) model size, however, the block size is governed by the size and spacing of the fractures (see Figures 3-9 and 3-10); this critical model size is estimated to have edge lengths of about 20 times the mean spacing.

In addition to the mean block size, the total volume of blocks formed is also dependent on model size.
Figure 5-1: Top: The same fracture network, clipped to boxes of A) 20m, B) 16m, C) 12m, and D) 8m. Bottom: the resultant blocks produced from the truncated fracture networks at various scales.

Effective evaluation and simulation of block sizes in a rockmass is required in order to optimize support designs for the expected blocks, to estimate design blocks for rockfall catchment systems, and as input to many classification systems. The latter is important as values from Q, RMR or GSI are commonly used as strength estimates in modeling. It is therefore important to understand how existing calculations compare to an overall block size distribution for a given set of parameters.

The most common problem with existing methods used to determine block size is that a single, representative “average” block is calculated. If it is accepted that rock fracture networks are typically composed of a range of fracture intensity and sizes, even within a single geotechnical domain, it then follows that the blocks formed by such fractures should also cover a range of values. By using the average intensity and average fracture size, the possibility for large blocks to form is disregarded. Equally important may be the presence of zones of very small blocks that
cannot be supported in the same way as a “medium” size block might be. Both extremes could be problematic if encountered unexpectedly in an excavation. Palmstrom (2005) suggested that the largest and smallest block size be reported, based on what is observed on a mapping face, to provide a range for consideration during design. While this is a much better approach, it should be understood that blocks larger than the mapping surface could be formed if a larger excavation is to be constructed. It also is dependent on the spacing in the out-of-plane direction being known or estimated.

To incorporate the distributions of fracture sizes and intensities encountered in a rockmass, DFNs have been used to create block size distributions, and estimates of “average” block sizes for a range of input values. From this, a preliminary estimate of what block sizes are likely to be encountered can be generated and designs tailored to an appropriate confidence interval for a given project.

This chapter compares existing estimators of block size to outputs from DFN modeling as well as suggesting a set of descriptive parameters for block size distribution curves. Block size distribution curves for different geometries are compared to block size estimates from empirical equations currently used in practice. Finally, a scale-independent method of incorporating fracture spacing and expected block size into the GSI chart is presented.

5.2 Comparison of Existing block size estimates

When characterizing the geometry of a rockmass, it is often relevant to determine the size of typical blocks formed by fractures or by the intersection of fractures with an excavation surface. These block size estimates can be used to examine support or protection requirements or may be used for fragmentation analysis for block caving operations. In addition to being used directly for design purposes, block sizes are also used indirectly in classification systems that use approximations of block size in assigning various strength and deformability properties to a rock mass.
Palmstrom (1996) suggested a block volume estimate, $V_b$, based on the average spacing of each of the identified fracture sets. It was stated that the mean spacing for each set be used, as averaging all set spacings together weights the wider spacings more heavily and produces a larger block size estimate. The resultant equation is thus, simply:

$$V_b^{N_{continuous}} = s_1 \times s_2 \times s_3$$  \hfill (5-1)$$

Where $s_i$ represents the mean spacing for a given fracture set.

To account for non-normal angles between the fracture sets, equation (5-1) was modified by Palmstrom (1996) as follows:

$$V_b^{N_{continuous}} = \frac{s_1 s_2 s_3}{\sin \gamma_1 \sin \gamma_2 \sin \gamma_3}$$ \hfill (5-2)$$

Where $\gamma_i$ represents the angle between the $i$th fracture set and the remaining fracture sets.

Equations (5-1) and (5-2) utilize only fracture spacing to determine block size and must assume fully continuous fractures, or at least fractures with size significantly greater than spaces between them; this is denoted here with the subscript “continuous”. When fractures are not continuous, the potential for larger, staircase-type blocks exists. The following equation incorporating non-continuous fractures was proposed by Cai et al (2004):

$$V_b = \frac{s_1 s_2 s_3}{\sin \gamma_1 \sin \gamma_2 \sin \gamma_3 l_i p_i p_2 p_3}$$ \hfill (5-3)$$

Where $p_i$ is a fracture persistence factor, defined as:

$$p_i = \begin{cases} l_i/L, l_i < L \\ 1, \quad l_i \geq L \end{cases}$$ \hfill (5-4)$$

Cai et al (2004) define $L$ as “the characteristic length of the rock mass under consideration”, and $l_i$ is defined as the accumulated joint length of set $i$. This definition appears to follow the definition of persistence presented by Dershowitz and Einstein (1988) “the sum of individual trace lengths relative to the length of a collinear scan line”. This parameter could be calculated from trace length data with some knowledge of the geometry of the sampling plane; however, it is
then defined by the size of the sampling plane, not by the geometry of the fracture network itself. While it is possible that the size of the excavation under consideration may impact the size of blocks that can detach, specifically when an excavation is too small to accommodate block detachment, the size of fracture-bounded blocks within a rock mass is not affected by the size of the excavation. It may therefore be more convenient to determine the overall natural block size distribution (i.e. those blocks formed by fractures in the rock) and then determine which block sizes should be included in support considerations.

The above equations are used to calculate a single representative block size for a rock mass. As a mean spacing is used for all of them, this indicates that an “average” block is being predicted; however, as fracture set spacing and fracture size distributions are variable, the blocks in a rock mass will cover a range of sizes. Palmstrom (2005) suggests measuring the largest and smallest blocks visible to provide a possible range, or selecting a representative block volume at the site in question. Others (Elmo, 2014, personal communication) have used Discrete Fracture Network (DFN) modeling to predict the range of block sizes and select the 80th or 90th percentile probable block volume created by the intersection of the fracture network with an excavation for design of support or protection measures. It is possible to use maximum and minimum spacing values in the above calculations to predict a range of block sizes that may exist in a given rock mass, though this does not provide the relative abundance of each block size.

For projects where estimated block size has a significant impact on the design, or where the rock mass geometry is complicated, a DFN model may provide a more complete picture of what can reasonably be expected to be encountered. The following section presents block size distributions generated from DFN modelling of theoretical rock masses having a range of fracture sizes and spacings. These block size distributions have been used as a simple block size estimation tool, where estimates may be incorporated into classification systems or used in other applications where the use of the equations above would be considered adequate.
To compare the results from the equations listed above with the mean block size determined from Discrete Fracture Networks, nine models with varying fracture size and spacing were created. All models assumed a negative exponential size distribution. The models were clipped to a cubic volume having sides 20 m long, equal to the critical size for the model with the largest spacing. Three orthogonal sets with a constant orientation distribution were used. The bounding box of the model was not included as fracture surfaces, thus only blocks bounded by generated fractures are included in the block size distribution curve determination. This means, as described in Chapter 3, that smaller diameter fractures may produce larger blocks on average, but fewer blocks in total. The distributions have all been normalized to the total volume of blocks formed, not to the total volume of the model space. Table 5-1, below, shows the size and spacing inputs for each of the models. A comparison between the values calculated using Equations (5-1) and (5-3) for each of the models and the 50th percentile block computed from the DFN block size analysis is also shown in Table 5-1.

Table 5-1: Model mean spacing and Equivalent Radius inputs used in this work. Expected Mean Block Sizes computed from Equations (1) and (3) and computed 50th percentile block from DFN modeling are shown.

<table>
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<tr>
<th>Model</th>
<th>Mean spacing</th>
<th>Mean Radius</th>
<th>Eq’n (1)</th>
<th>Eq’n (3)</th>
<th>50th percentile DFN Vol</th>
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<td></td>
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<tr>
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<td>0.053</td>
<td>0.032</td>
</tr>
<tr>
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<td>5</td>
<td>0.008</td>
<td>0.021</td>
<td>0.032</td>
</tr>
</tbody>
</table>
Equations (5-1) and (5-2) produce identical results as the fracture sets are normal to one another; thus results from Equation (5-2) are not shown here. For Equation (5-3) it was assumed that $l_i$ was equal to 1.5 times the mean equivalent radius, as an approximation of the expected mean measured trace length, and that $L$ was equal to the side length of the model (20 m); a $p_i$ value of 1 would produce the same results as Equations (5-1) and (5-2).

Figure 5-2 shows the block size distribution curves for the 9 models listed in Table 5-1. The block size estimates from Table 5-1 are plotted for comparison with the corresponding distribution curves.

**Figure 5-2:** Block size distribution curves for the models described in Table 5-1. Square and circle markers indicate values from Equations (5-1) and (5-3), respectively. They are plotted along the 50th percentile line for comparison to the mean value of the distribution curves. The marker colours correspond to the related distribution curve.

It is evident that Equations (5-1) and (5-2) provide a poor approximation of block size, even when fracture size is significantly larger than the mean spacing, the conditions that best approximate continuous fractures. This is likely because fracture spacings are generally found to follow a negative exponential distribution (Hudson and Priest, 1979; Priest and Hudson, 1976; Baecher,
and wider spacings can produce a limited number of larger blocks that account for a much larger portion of the total block volume and therefore shift the mean block size to the right. Equation (5-3) shows a better correlation with the DFN results for many of the models, but does poorly when the fractures become very small relative to their spacing. This is likely because the equation does not account for the possibility that small fractures rarely intersect each other when they are widely spaced.

Alternative assumptions regarding the calculation of the $p_i$ value could also have produced results closer to those produced through DFN modelling, but these are not investigated here.

The most commonly used block size estimators can be separated into those used for block volume calculations, and those that are used within a rockmass characterization system. As mentioned above, these estimators have significance not only in instances where block size is being expressly considered, but are also incorporated indirectly into strength and deformability estimates to be used in modeling. These strength estimators are well summarized by Palmstrom (2005) as follows:

- $\frac{RQD}{Jn}$ (where $Jn$ is a coefficient for the number of joints) in the Q system
- $RQD$ and $S$ (joint spacing coefficient) in RMR
- $V_b$ in the RMi system

Block size is also incorporated more descriptively in the GSI chart.

### 5.3 Relating block size distributions to fracture intensity and size

As shown above, the commonly used equations for computing block size are unable to effectively account for the impact of fracture size on block size distribution. To determine where these equations might be most useful, the 50th percentile block sizes were normalized to mean spacing using the following equation:

$$V_{50Normalized} = \frac{\sqrt[3]{V_{50}}}{mean\ spacing}$$  \hspace{1cm} (5-5)
Where $V_{50}$ is the mean 50th percentile block computed from 5 realizations of each model.

The $V_x$ notation is used here to denote the percentile volume rather than the $P_x$ notation that is sometimes used to avoid confusion between volume percentiles and fracture intensity.

The fracture size was also normalized to the mean spacing value using the following equation:

$$ Fracture \ Area_{Normalized} = \frac{\sqrt{\text{mean\ fracture\ area}}}{\text{mean\ spacing}} $$

(5-6)

This was repeated for models with the same size and spacing inputs, using 3 additional size distribution types. The results are shown in Figure 5-3, below.

![Figure 5-3](image)

**Figure 5-3:** Plot showing the mean block size, normalized to spacing, for various fracture size to spacing ratios, and four of the statistical distribution models available within FracMan.

Figure 5-3 shows much more variation in block size when the fracture size is within an order of magnitude of the mean spacing. When fractures are larger than about 10 times the spacing, the computed block sizes become much more consistent. It is assumed that when fractures are more than an order of magnitude larger than the spaces between them, they can be considered continuous. However, for all distribution types, the mean block size for continuous fractures is
about 1.6 times the normalized block size. The plot also shows a maximum block size occurring when the fracture size is around 3.5 times the spacing for a negative exponential distribution and about 7 times the spacing for the other three distributions.

The negative exponential fracture size distribution produces a much greater variation than the others considered here. By definition, the standard deviation of an exponential distribution is equivalent to its mean; thus a small number of very large fractures can be generated, even when the mean fracture size is small. For the other distributions considered, a standard deviation equal to 25% of the mean radius was used, as this was assumed to be more typical of normal distributions. The input variability parameters for the log normal and power law distributions were input to be similar to those from the normal distribution. The results from these 3 distributions are very similar, indicating that the presence of a few large fractures can have a much greater impact on block size than many smaller fractures. The results also indicate that the selection of fracture size distribution type is of little importance in determining block size, provided the variability of that distribution is accurately represented.

As described above, where the same intensity was used, the total fracture area within the model was approximately the same, but was divided among different sized fractures depending on the size specified and the distribution used.

When planning support or catchment for rock excavations, it is often more appropriate to use a larger block size for design purposes. The 80th and 90th percentile block volumes were selected from each of the models presented above to produce the plots shown in Figure 5-4 and Figure 5-5.
Figure 5-4: Plot showing the expected 80th percentile block size, normalized to spacing, for various fracture size to spacing ratios.

Figure 5-5: Plot showing the expected 90th percentile block size, normalized to spacing, for various fracture size to spacing ratios.

The above plots exhibit a similar pattern to the 50th percentile plot although the scale of the vertical axis is increased and there is amplified variability in the block size produced by the negative exponential distribution when fracture size is about 3.5 times larger than spacing.
5.4 Additional parameters to describe block size distribution

Further parameters describing the rock mass distribution curve would add to the utility of using a mean block size such as that described above. Two parameters common in soil classification, the coefficient of uniformity, $C_u$, and the coefficient of curvature, $C_c$, were evaluated for the curves shown in Figure 5-2.

The coefficient of uniformity is defined as follows (from Das, 1999):

$$C_u = \frac{V_{60}}{V_{10}}$$

(5-7)

Where block volumes are denoted as described above.

The coefficient of curvature, $C_c$, is defined as follows (from Das, 1999):

$$C_c = \frac{(V_{30})^2}{V_{10} \times V_{60}}$$

(5-8)

It is noted that in soil mechanics, these values reference particle diameters, not volumes. The results from these calculations are shown in Figure 5-6 and Figure 5-7, below.

![Figure 5-6: Calculated $C_u$ values for the curves shown in Figure 5-2.](image)
Figure 5-7: Calculated $C_c$ values for the curves shown in Figure 5-2.

From the above figures, the $C_u$ values have a downward trend as fracture area is increased relative to spacing; this is most pronounced for the exponential distribution while the other distributions appear to reduce scatter as fracture size is increased. As the $C_u$ value describes how uniform a sample is; specifically how close in size the 60th percentile block is to the 10th percentile block, it fits with previously described results that larger fractures with smaller spacings have more uniform distributions, defined by the spacings, while shorter fractures produce more erratic results with some very big blocks and many smaller ones.

No definitive pattern is evident in the $C_c$ values, though they appear to vary about a value of 1. In traditional soil mechanics, a $C_u$ value greater than 4 for combined with a $C_c$ value between 1 and 3 indicates a well-graded material. If these criteria are not met, the material would be considered to be poorly graded, or well sorted (Das, 1999).

All models examined have a $C_u$ value greater than 4 and many of the $C_c$ values are close to one, indicating, by soil mechanics standards, a well graded material; however, as no dominant trend is visible in the $C_c$ data, it is difficult to suggest a general distribution curve shape based on fracture
size and spacing alone from these models. A more extensive set of models might produce a more observable trend, but this is not explored further here.

An additional classification parameter to account for scale, and the existence of "intact rock", i.e. rock mass not bounded by fractures, was also considered. A similar parameter does not exist in soil classification. Generally, as a sample size or excavation gets larger, more fractures will be intersected creating more and possibly larger blocks. Smaller samples intersect fewer fractures and therefore form fewer blocks, leaving much more intact rock mass. In DFN modeling, some of this can be attributed to edge effects; however, the edge effects may serve as an analogy to issues of scale in practice. Specifically, if an excavation is smaller than the blocks surrounding it, those blocks may be considered as intact for that project. Additionally, not all intact rock generated in DFN models can be explained by model boundaries. For short fractures with large spacing, it is logical to assume that, at any scale, a significant portion of intact rock exists.

As illustrated in Chapter 3, when fractures are not continuous, only a portion of the model volume actually forms blocks. For the models described in Table 5-1, a plot comparing the normalized mean block size to the fraction of the model that is intact was produced (Figure 5-8). It should be noted that the relationships in this figure are sensitive to model scale. While much larger models should produce similar results, smaller volumes for these models produce significant variability. This figure is included to show that the normalized mean block size relates to the total volume of blocks that can form. However, due to the single model size considered, no specific conclusions relating fraction of intact rock, mean block size and excavation extents are made here. As with the Cc plot, a greater number of data points are required to make more quantitative inferences.
It is noted that these relationships have been calculated using only 3 fracture sets, all oriented at right angles, having the same size and spacing values for all sets. All block size analysis was done assuming a cube with 20 m long sides. Incorporating a greater range of variables, particularly of variability of size and spacing fractures for different sets, into a similar chart would be very useful, but is beyond the scope of this work.

It is further noted that these charts are not intend to replace detailed modelling for complex projects, but rather as an alternate or complement to Equations (5-1) to (5-3) for applications where these would provide an adequate degree of accuracy.

5.5 A proposed scale for the “B” axis of the GSI chart

The most recently published update to the GSI chart (Hoek et al, 2013) provided a simplified relationship between the discontinuity surface condition rating – the x axis – and the blockiness of the rockmass – the y axis. While the x axis is less sensitive to scale – a smooth, altered joint surface is poor quality, regardless of scale – the y axis should be representative of how blocky the rockmass is at the scale of the excavation.
The suggested range for the y axis is RQD/2, with an upper limit of 40 (RQD of 80). This value is easily computed from widely available data and is practical for many applications. Previously Cai et al. (2004) suggested a set block volume for each vertical division on the GSI chart. Tzamos and Sofianos (2007) used the mean block size suggested by Cai et al. (2004) to compute a range of spacing values corresponding with each block size interval.

All of these values may be useful for a given project, and can be applied consistently by less experienced personnel; however, one of the greatest advantages of the GSI chart is that it can be used by veteran practitioners at any project scale. Thus the overall blockiness of the rockmass need not only relate to the size of the blocks formed, but also how those blocks compare to the size of the excavation. The use of conventional RQD, that is an RQD value based on a threshold value of 0.1 m, is limited in utility to rockmasses with spacings of 0.3 m or less. Priest and Hudson (1976) showed that for mean spacing values larger than 0.3 m, RQD would be no less than 95% for adequately large samples. A modified RQD, indicated as RQD* as per Priest and Hudson, with threshold values adjusted according to the scale of the excavation and/or the degree of fracturing in a rockmass, could be used to make the vertical axis of the GSI chart relate to the excavation in question.

The RQD* value, however, has limitations; specifically that skilled practitioners have a sense of how conventional RQD values relate to real rockmasses, from their experience. If the RQD* scale is continually being adjusted, this intuitive sense of fracturing is lost. Priest and Hudson suggested presenting both the conventional RQD alongside the modified RQD* so that both the historical familiarity and site specific extension of the scale can provide a more complete picture. For very large spacings, RQD* encounters problems with data collection; borehole investigations may be limited by core barrel lengths, while to determine an accurate RQD from wall mapping it has been suggested that a sample size of 20 to 50 times the fracture frequency (Sen and Kazi,
(1984; Priest and Hudson, 1976) be taken to minimize sample error, requiring very long sample lines. Finally, RQD is a linear measure and is therefore subject to orientation bias. An alternate y axis that remains scale-independent can be proposed based on Figure 5-2 and the relationship between fracture spacing at various RQD ratings and the suggested upper limits of the scale. It is expressly stated in Hoek et al. (2013) that GSI should only be used when the rockmass is homogeneous and isotropic and that more massive rock does not meet these requirements; thus if mean fracture size is not greater than 10 times the spacing, the GSI chart may not be appropriate. Further, the chart presented in 2013 suggests limiting the use of the chart to tunnels with spans of 10 m or less or slopes no taller than 20 m. Assuming a negative exponential distribution of spacings, the following equation from Priest and Hudson (1976) relates the RQD value for a given threshold value and mean spacing:

\[ RQD = e^{-\lambda t} (1 - \lambda t) \]  

(5-9)

Where \( t \) is the RQD threshold value, assumed to be 0.1m, and \( \lambda \) is the fracture frequency. Using the y axis RQD values, the mean spacing was calculated from Equation (5-9). These spacing values were then used to derive a ratio between mean fracture spacing and the suggested upper limits for tunnel span and slope height. The calculated ratios are presented alongside the RQD/2 scale in Figure 5-9. The presented scales provide relative, rather than absolute, sizes and can be applied consistently by less experienced personnel. Though Section 5.3 suggests using spacing and fracture size measurements to estimate \( V_{50} \), a visual approximation of mean block size could be used to allow GSI to be assessed in the field. The visual approximation of block size could later be compared to trace length data and the GSI value adjusted if/as appropriate. This would be most applicable when only small windows are available to characterize the rockmass for a large project.
5.6 Summary and Conclusions

This chapter has shown that fracture size can play a significant role in the determination of an appropriate mean block size for a given rockmass. DFN modelling using the FracMan code was used to show that for 3 sets of orthogonal fractures with equal spacings and fracture sizes, continuous fractures will produce blocks about 4 times ($1.6^3$) larger than simply multiplying the spacings. It was also shown that, for block size distribution purposes, a fracture set could be considered continuous if its mean size is about 10 times the set spacing. Modelling showed that
fractures slightly smaller than 10 times the spacing produce the largest mean block sizes; however the total volume of blocks formed is less than when fractures are larger. When fractures are very small relative to the spaces between them, the fractures are less likely to intersect one another at all and thus mean block size and total volume of blocks are reduced.

The size distribution curve parameters Cu and Cc used in soil mechanics were evaluated for use in block size distribution charts. While these parameters may be generally useful, no definitive pattern allowing a general quantification was possible from the models considered.

Using the relationship between mean fracture spacing and RQD, a relative scale for the GSI chart Y axis was proposed to allow GSI values to be determined simply, by less experienced personnel while still considering the relative size of blocks compared to the excavation.

Further modelling incorporating variability between fracture sets, in terms of spacing and size, as well as using different fracture shapes could help extend the applicability of these results. Chapter 6 will investigate the applicability of these charts using real data to compare the computed block size from the plots presented here to those actually measured in the field.
Chapter 6

Practical Applications

The following Chapter was written in collaboration with Cara Kennedy who provided the photogrammetry data and images as well as providing input on the text relating to the generation and use of photogrammetric models.

6.1 Introduction

In order to test the block size estimation charts against real data, a test site from Red Rock, Ontario was used. Input parameters for the DFN models were selected both semi-automatically in the 3DMAnalyst software package as well as through a virtual window mapping of the surface generated through photogrammetric methods. The data from the different data collection methods were then used to generate DFNS to predict the range of block sizes that were likely to occur along the slope. This chapter discusses, briefly, the generation of the photogrammetric surfaces, the sampling methods used on the surface and provides a comparison of the rock blocks generated from the data collected from each model type. The modelled blocks are also compared to the theoretical block size estimate presented in Chapter 5.

6.2 Development of DTM

The slope was photographed from approximately 20 m from the base of the slope using a Nikon D800, full frame, digital single reflex camera (DSLR). The photos were then imported in to the ADAMTechnology software tool, CalibCam, where Digital Terrain Models (DTMs) were constructed for analysis is 3DM Analyst. From within 3DM Analyst several DTMs were merged into one DTM from various viewing orientations to prepare the models for discontinuity analysis; a primary “head on” DTM, and two oblique views, one from either side. The oblique DTMs provided improved visibility and model generation of surfaces that were normal to the head on
view and would not otherwise be adequately captured. The head-on DTM is shown below in Figure 6-1.

**Figure 6-1: Head-on DTM of Red Rock, Ontario slope.**

The surface has a dip of about 81 degrees and strikes slightly off of west at 248 degrees. From the DTMs, a limited region, measuring about 48 m long by 15 m high, was identified as being the source zone of rock fall blocks from an event that occurred in the summer of 2012. This area is the focus of this work and data collection is limited to this region. It is shown, along with detected discontinuity surfaces, in Figure 6-2, below.
6.3 Parameter Selection

From these DTMs, 3DM Analyst was used to automatically detect surfaces where the diameter of the circle enclosing the surface is greater than 0.4 m, which was determined as being an appropriate tolerance through a parametric analysis. Surfaces, for the purposes of 3DM Analyst, are formed when adjacent points forming the nodes on the DTM are added to a surface if they meet the maximum angle and height ("point") offset tolerances set to define a plane. For this project, a 0.035 m threshold was used for the point offset and 13 degrees was used for the angle offset – again determined through a parametric analysis. Large triangles generated in areas where the point density was sparse or triangles meshed irregularly due to the viewing orientation that are not representative of the in-situ conditions must be cleaned manually.

For the semi-automatic discontinuity analysis, the user selects planes from the DTM – to be used as reference planes – that are the most representative of the structure within the study zones. From there a joint subsetting procedure is executed within the software program where faces within a user-defined orientation tolerance are grouped in sets – a 15 degree range from the user-defined plane pole was used. The user may also manually create surfaces to be added to analyses. The software measures the maximum chord and surface area as well as the dip and dip direction.

Figure 6-2: Head on view showing detected faces in the region of interest.
of the detected faces. The region selected for analysis is considered to be a single geotechnical domain, and the parameters collected are assumed to be approximately constant across the region in question.

6.3.1 Semi-Automatic selection

To compare the automatic face detection algorithm with manual methods, the data selection process was first run with minimal user input. The face size, angle and point offset limits were input, and four surfaces identified as the base for set groupings. The detected face orientations were then input into Dips to determine a mean set orientation and to determine an appropriate orientation distribution and variation parameters. As there were 3 DTMs covering the same region, the data generated from each was compared; the data from each set was collected from the DTM that best represented that set – based on the maximum number of joints being created. The resulting stereonet is shown below, in Figure 6-3.

Figure 6-3: Stereonet showing orientation data from semi-automatically detected faces and the mean set planes for the identified sets.
As 3DM Analyst does not output an intensity parameter, the P<sub>10</sub> value was estimated using the mean from 3 synthetic sample lines for each set. The lines were oriented approximately parallel to the slope to maximize intersections with identified fracture surfaces on the DTM. The maximum chord lengths of each surface from the auto-detect output were used to evaluate fracture size distributions and calculate the mean fracture size for each set. The P<sub>10</sub> values are shown in Table 6-1 below, along with the mean set orientation computed in Dips and the mean maximum chord length measured for each fracture.

**Table 6-1: Input parameters derived from automatically selected surfaces**

<table>
<thead>
<tr>
<th></th>
<th>Set 1</th>
<th>Set 2</th>
<th>Set 3</th>
<th>Set 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Orientation (Dip/dip dir’n)</td>
<td>88/183</td>
<td>89/119</td>
<td>17/094</td>
<td>87/154</td>
</tr>
<tr>
<td>Fisher K value</td>
<td>95</td>
<td>85</td>
<td>100</td>
<td>79</td>
</tr>
<tr>
<td>P&lt;sub&gt;10&lt;/sub&gt;</td>
<td>0.38</td>
<td>0.17</td>
<td>0.75</td>
<td>0.4</td>
</tr>
<tr>
<td>Mean Length (m)</td>
<td>0.66</td>
<td>0.64</td>
<td>5.5</td>
<td>0.67</td>
</tr>
</tbody>
</table>

These parameters were used to construct a DFN model. Following the information presented in Chapter 4, indicating that fracture traces represent about 1.5 times the mean fracture radius, models were run with the mean equivalent radius input assumed to be 75% of the measured mean maximum chord length. However, because photogrammetric methods are only able to identify faces, and do not incorporate traces extending beyond the face – even if these are clearly discernible – an additional model was generated where full extent of the chord length assumed to be the mean radius. The results from each of these models are discussed in Section 6.5.1, below.

**6.3.2 Manual Rectangular window**

To simulate more conventional window mapping methods, a smaller region, measuring 10 m high and 8 m wide, was selected for detailed manual mapping. This area was selected to encompass
an area larger than the rockfall zone area – but including the rockfall zone area itself – as this zone contains minimal large and irregular triangles, and is structurally relevant to the rockfall zone. Each surface having a max chord over 0.30 m and that is visible in the region was traced to generate the orientation and maximum chord length data to be used in DFN generation.

The orientation data from the selected surfaces is shown in the stereonet shown in Figure 6-4, below. When compared to the automatically selected data shown above, good agreement between stereonets and mean set orientations is observed.

Figure 6-4: Stereonet showing orientation data from manually selected faces and the mean set planes for the identified sets.

The intensity data was again derived from synthetic sample lines within the detailed mapping regions. The data used to generate the DFNs for the model based on this manually selected data is shown in Table 6-2 below.
Table 6-2: Input parameters from virtual window mapping data

<table>
<thead>
<tr>
<th></th>
<th>Set 1</th>
<th>Set 2</th>
<th>Set 3</th>
<th>Set 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Orientation</td>
<td>86/184</td>
<td>87/119</td>
<td>25/111</td>
<td>89/152</td>
</tr>
<tr>
<td>(Dip/Dip dir’n)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fisher K value</td>
<td>65</td>
<td>126</td>
<td>101</td>
<td>38</td>
</tr>
<tr>
<td>P_{10}</td>
<td>0.6</td>
<td>0.36</td>
<td>0.28</td>
<td>0.62</td>
</tr>
<tr>
<td>Mean Length (m)</td>
<td>1.13</td>
<td>0.86</td>
<td>2.13</td>
<td>0.86</td>
</tr>
</tbody>
</table>

It should be noted that the P_{10} value does not account for directional bias. As photogrammetry selects faces rather than traces, surfaces sub-parallel to the face are more likely to be sampled than they would be in normal scanline or borehole logging. Further, as linear traces that are sub-normal to the mapping face do not produce a significant number of surfaces, the usual sample bias is assumed not to apply here. Due to the 2.5D nature of the surface, scanlines cannot sample data into the surface. P_{21} values were also examined, but these were calculated to be between 25% and 50% of the unweighted P_{10} values. As discussed in earlier chapters, the P_{21} value is more subjective than other measures of fracture intensity, and the unweighted P_{10} values were used based on a visual check of the generated DFN to the DTM and photos from the site.

It is also worth noting that the mean fracture sizes are, on average, larger than those detected in the semi-automatic face detection.

The results from this model are discussed in Section 6.5.2, below.

6.4 Generation of models

To compare the DFNs created from the inputs described above, the rock block function in FracMan was used. This function takes fractures intersecting a user-defined plane and detects if other intersecting fractures will form a block daylighting on the selected face. Unlike the block
size distributions analyzed in the preceding chapters, this function considers only the blocks formed along a surface; the overall rockmass block size distribution is not considered. As such, the total volume of blocks formed is much less relevant and the mean block size ($V_{50}$) or design block size ($V_{80}$ or $V_{90}$) are likely to be of much greater interest and utility.

Fracture surface strength parameters can be defined to calculate a factor of safety for each block. For the purpose of this study, only the block volume was evaluated. The stability was not considered, and thus the determination of fracture strength parameters was not required. It should be noted that fracture surface parameters are much more difficult, if not impossible, to collect reliably from remote methods at this time. At-the-face mapping is recommended if this functionality is to be used.

Five surfaces, having the same dimensions and orientation as the sampled zone, were created to evaluate the blocks formed in 5 realizations of each model. Three additional, taller surfaces, having a height of 80 m, approximately twice the height of the slope under consideration, were also considered to include the potential for very large blocks. The surfaces are shown in the model space in Figure 6-5, below.

![Surfaces used to evaluate volume of rock blocks formed.](image-url)

**Figure 6-5:** Surfaces used to evaluate volume of rock blocks formed.
The statistics and block volumes from each realization on each surface were recorded. Composite blocks, where two or more blocks could be grouped together as a single mass, were also included in these analyses. Block volume distribution curves are presented for each model for both the composite and singular blocks, in the following sections.

6.5 Results from Models

6.5.1 Semi-automatically detected faces
As described above, there were two models developed for the semi-automatically detected faces, one with the equivalent radius equal to the measured maximum chord size, and one using 75% of the measured mean maximum chord size to account for truncation and censoring error. The blocks formed from each realization on a given surface were grouped together and block size distribution curves were developed. These were normalized to the total volume of blocks formed. Figure 6-6, below, shows the curves for each of the 8 surfaces as well as the mean and median values from all 8 surfaces combined.

The curves from the taller surfaces are smoother and have larger blocks, on average, than those from the surfaces of the same dimensions as the sample area. The composite block curves appear stepped, owing to the occurrence of a limited number of larger blocks. There is also greater variability between surfaces on the composite block curve.

Figure 6-7 shows the same data, but for the model using 75% of the mean maximum chord length as the input radius. The 75% value was selected based on the work shown in Chapter 4, where sampled trace lengths are shown to have an expected value of about 75% of the true fracture diameter. As the surface size values were already biased towards shorter measurements due to the limitations of photogrammetric data, the results from the shorter data show significant variation between surfaces. More realizations might be appropriate for a model showing this degree of variability to increase confidence in the calculated $V_{50}$ value.
Figure 6-6: Block size distribution curves for automatically detected faces, using the mean maximum chord length for each set as the mean radius. The curves for single blocks (top) and composite blocks (bottom) are shown.

A sample surface showing fracture traces and composite blocks connected to the face for each of the models is shown next to an image of the DTM used to determine input parameters in Figure 6-8 and Figure 6-9. Due to the selection of a single, long sub-horizontal fracture to define Set 3, this set appears over-represented in both of the DFN trace maps.
Figure 6-7: Block size distribution curves for automatically detected faces, using 75% of the mean maximum chord length for each set as the mean radius. The curves for single blocks (top) and composite blocks (bottom) are shown.

The shorter fractures in the model shown in Figure 6-9, do not allow many blocks to form and this model is not representative of what is observed in the DTM. The blocks visible in Figure 6-8 appear much closer to what can be seen. As mentioned above, all blocks formed along the traceplane are included, regardless of stability; thus the improbable block geometries shown would not necessarily be expected to be unstable.
Figure 6-8: Comparison of (A) semi-automatically detected photogrammetry data, (B) generated fracture traces and blocks and (C) a "behind the scenes" view of the blocks connected to the selected surface. The DFN data represents the model using the mean max chord length as the mean radius.

Figure 6-9: Comparison of (A) semi-automatically detected photogrammetry data, (B) generated fracture traces and blocks and (C) a "behind the scenes" view of the blocks connected to the selected surface. The DFN data represents the model using 75% of the mean max chord length as the mean radius.
6.5.2 Virtual rectangular mapping window

As described above, a DFN was created from the data from the manually selected surfaces in the virtual mapping window. The mean max measured chord was used as the input for the mean radius for each set as the results from the automatically detected data indicated poorer results for the model using only 75% of the measured chord length. Despite improved fracture size data, it is assumed that the photogrammetric data is still skewed towards shorter surfaces. As above, the blocks formed from each realization on a given surface were grouped together and block size distribution curves were developed. These were normalized to the total volume of blocks formed. A sample surface showing fracture traces and composite blocks connected to the face for this model is shown next to a close-up of the virtual mapping window on the DTM in Figure 6-10.

Figure 6-10: Comparison of (A) manually selected planes in virtual mapping window, outlined in blue, (B) generated fracture traces and blocks on a selected surface and (C) a "behind the scenes" view of the blocks connected to the selected surface.

Figure 6-11, below, shows the curves for each of the 8 surfaces as well as the mean and median values from all 8 surfaces combined. The curves generated for these surfaces are much smoother
and more consistent than those from the automatically detected faces. This is likely as a result of a greater number of blocks being formed because the input mean radius for 3 of the 4 sets were longer, creating an increased probability of fracture intersection. This is seen in the increased number and volume of blocks formed visible in Figure 6-10.

![Block size distribution curves for manually selected faces. The curves for single blocks (top) and composite blocks (bottom) are shown.](image-url)
6.5.3 Comparison of models to other block size prediction methods

The blocks generated were compared to the empirical equations put forth by Palmstrom (1996) and Cai et al. (2004), numbered Equations (5-1) and (5-3) in Chapter 5, respectively, and were also compared to the expected volume derived from the plot found in Fig 5-3 of this work. For simplification of calculations, sets 1 and 4 from both data sets were merged together.

The spacing was calculated from the $P_{10}$ values shown above. For an estimate of $p$, the variable used to account for fracture persistence, it was assumed that the set length was equal to the mean measured maximum chord and that the characteristic length was assumed to be 15 m for the sub-vertical sets from the automatically detected window, 10 m for the sub-vertical sets from the manually selected virtual window, 48 m for the sub-horizontal set in the automated window and 8 m for the sub-horizontal set in the manually selected virtual window (see Chapters 2 and 5 for equations and further details).

To use the plot estimating mean block size from the ratio of mean fracture size to mean spacing presented in Chapter 5, it was necessary to determine appropriate mean size and spacing values, as these models used nonhomogeneous fracture parameters. The mean spacing value was calculated as follows:

$$S_{\text{mean}} = \sqrt[3]{S_1 S_2 S_3} \quad (6-1)$$

Where $s_i$ represents the mean spacing of the $i$th set.

The mean radius was determined as follows:

$$R_{\text{mean}} = \sqrt[3]{\frac{R_1^3 + R_2^3 + R_3^3}{3}} \quad (6-2)$$

Where $R_i$ represents the mean radius for the $i$th set.

From the above equations, the relationship between mean spacing and mean fracture size was calculated and the resultant mean spacing multiplier read off from Figure 5-3. The values from each of these methods are compared with the computed $V_{50}$ from the models in Table 6-3, below.
Table 6-3: Summary of mean block sizes

<table>
<thead>
<tr>
<th></th>
<th>$V_{50}$ single</th>
<th>$V_{50}$ Composite</th>
<th>Eq’n (5-1)</th>
<th>Eq’n (5-3)</th>
<th>Fig 5-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto-detected model</td>
<td>1.86</td>
<td>2.52</td>
<td>0.05</td>
<td>545</td>
<td>2.52</td>
</tr>
<tr>
<td>75% length auto-</td>
<td>0.68</td>
<td>0.89</td>
<td>0.05</td>
<td>400</td>
<td>1.29</td>
</tr>
<tr>
<td>detected model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Virtual mapping</td>
<td>2.66</td>
<td>3.32</td>
<td>0.06</td>
<td>150</td>
<td>0.69</td>
</tr>
<tr>
<td>window model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The mean curves for single and composite blocks are shown in Figure 6-12, below. The figure and the table show that the calculated values from both Cai et al. (2004) and Palmstom (1996) are poor estimates of mean block size, while the estimate from Figure 5-3 is much closer to the modelled mean. The estimate for the virtual window mapping is a poorer match than the others, likely as a result of the wider spacing and the shorter length of sub-horizontal Set 3. Equations (6-1) and (6-2) may not be the best way of relating non-homogeneous sets to the plot from Figure 5-3, but further modeling is required to determine if this is the case.

Figure 6-12: Block size distribution curves for the 3 models evaluated along with mean block size predictions from Eq'ns (5-1), (5-3), and Fig 5-3
6.6 Conclusions

The DFNs and rock block analysis generated from photogrammetric data illustrated some of the limitations of using DTMs to derive DFN input parameters. Particularly, DTMs limit fracture size estimation to visible surfaces only, even when traces extending past a surface are visible. This skews the mean fracture size towards shorter fractures than what might be mapped on site. This discrepancy was found to be less pronounced when fracture surfaces were manually selected. Many of the biases discussed in Chapter 4 do not apply or apply differently when data collected from remote sources that rely on fracture surfaces rather than fracture traces are used.

Despite the limitations of the data collection methods examined here, it was found that the mean block size predicted using the plot shown in Figure 5-3, is much closer to the mean block size generated in FracMan. While further tests of this plot are required, this result is encouraging as it indicates good results even when fracture sets are nonhomogeneous and that only blocks formed along a surface, as opposed to overall fragmentation, may also be estimated using this method.
Chapter 7
Conclusions and Future Work

7.1 Summary of Thesis
This thesis investigated the variables involved in building a Discrete Fracture Network model in order to provide insight into the decisions and assumptions made during the modeling process. This was divided into three main parts:

- assumptions within the FracMan DFN software pertaining to model selection and construction;
- biases and assumptions relating to field data and how it is collected that may impact the development of DFN input parameters
- the limits of the effects of these models on block size determination

An example using data from a real site was also undertaken to compare real data to the methods and described in this work.

7.2 Findings regarding model construction
The most relevant conclusions pertaining to model construction and sampling are as follows:

- The boundaries of the model should extend to about 20 times the largest mean spacing to generate consistent block size analysis results.
- Provided the model volume is adequately large, five realizations appear to be adequate for developing a reasonable prediction of block size. If the model is smaller than the recommended size, it was found that results were highly variable and it is suggested that in cases where it is not possible to construct a model 20 times the largest mean spacing value, that more models be run until a suitable average is discernible.
- The inclusion of the bounding box in block size calculations can have a significant impact on mean block size in models where fractures are moderately to widely spaced.
relative to their size as artificially large blocks are allowed to form. When fractures are much larger than the spaces between them, the inclusion of the bounding box surface in the block size calculation appears to have little impact on the overall block size distribution.

These findings were relatively consistent throughout the models tested, but the models were by no means exhaustive.

7.2.1 Future work on model construction
The parameters investigated here were limited to the most general cases, in a simplified rockmass. Assessing the findings described above for different model generation types, different fracture size distribution types and for models with non-homogeneous, non-orthogonal joint sets would increase confidence in the conclusions listed in Section Findings 7.2, above. Developing formal stopping criteria for the total number of realizations that should be run should also be considered, particularly for smaller models exhibiting a high degree of variability between realizations.

7.3 Findings regarding sample bias
The biases and limitations of data describing a 3D network, collected in 1D or 2D, were investigated by sampling a DFN of known parameters with a range of sample lines and trace planes to compare empirical relationships regarding orientation bias to virtual data. The main findings are as follows:

- Negative exponential fracture size distributions with short fractures relative to their spacing show a significant deviation from expected fracture frequency data along scanlines with optimized orientations (i.e. intersecting the greatest number of fractures). Models with larger fractures or with other distribution types did not show significant variance from the expected values.
• RQD, like fracture frequency, is directionally biased, but is less sensitive to orientation bias than the fracture frequency count. RQD, however, only provides meaningful values for rock masses where the mean fracture spacing is about 0.3 m, or less. At wider spacings, the expected RQD value is 95% or greater.

• Summing together the fracture frequencies of all fracture sets under consideration provided an estimate of volumetric intensity, \( P_{32} \), within 10% of the measured value, with the exception of the models with negative exponential fracture size distributions and larger mean fracture size.

• Large fractures are disproportionately sampled, both because they are more likely to intersect the sample plane and because when sample planes are close together large fractures may be counted on each surface where they appear, thus making the total count of large fractures larger than reality. This skews the sample mean trace length towards larger fractures.

• While large fractures are more likely to be sampled, their traces are also more likely to be censored. Their measured lengths are limited by the size of the sampling window. If the shorter measured trace lengths are used to calculate mean fracture size, the mean is skewed towards smaller values.

• Without truncation bias, the ratio between mean trace length and mean fracture radius was shown to be 1.7.

• For 3 of the 4 distribution types examined, the ratio between measured trace length and actual mean radius was about 1.5, indicating that the censoring of large fractures had a greater impact on the mean than oversampling of large fractures. However, for the negative exponential distribution, which had more large fractures than the other distributions, the ratio was between 2.2 and 3.6. This discrepancy is assumed to be due to the very heavy weighting of a limited number of large fractures that are counted each
time they intersect a sample plane, up to 48 times. Due to the larger number of large fractures in the negative exponential distribution, this effect is heavily pronounced.

- When small sample regions were used, data could be skewed or could be completely absent, such as not having any fractures from a set appear within the window. It is thus imperative that sample windows are selected to incorporate a representative area whenever possible.

- While generated models should be compared to their input parameters, this is not sufficient for ensuring the model matches in situ conditions as the input data is subject to sample biases that may or may not have been appropriately accounted for. Whenever possible, the model should be visually compared to the in-situ conditions.

### 7.3.1 Future Work regarding sample bias

A better understanding of sampling bias, particularly with mapped data and trace lengths would provide greater confidence in models containing DFNs. A database of sampled fracture sizes from a large number of sites, while not necessarily devoid of the biases described, would be useful in developing reasonable assumptions about fracture size distributions. This could be complemented by numerical modeling to develop estimates of expected distributions, particularly in areas with complex stress histories where existing fractures and faults are re-activated.

As field data often contains much more borehole data than mapping data, it would be useful to find a more reliable correlation between either parameters that can be measured in a borehole, and/or between limited mapping data and more extensive borehole data. This again would require case studies from a wide range of settings to develop and test any relationships that might be seen to emerge.

### 7.4 Findings regarding impact of assumptions on model outputs

Because fracture sizes and spacings tend to cover a range of values, so to do the block sizes formed by the intersection of these fractures. The relationship between fracture size and fracture
spacing is critical in determining block size, up to some point, where fractures are large enough relative to their spacings that they may be considered continuous. The following are the main findings regarding the impact of assumptions made when building DFNs on the estimated block size:

- Small fractures relative to spaces between them intersect rarely, thus are unlikely to intersect multiple fractures to create stepped blocks. The block size is therefore limited by the fracture size (not spacing) and the total volume of fracture-bounded blocks is small.

- Large fractures relative to the spaces between them intersect consistently, creating a large volume of fracture-bounded blocks. Block size is controlled by the spacings between the large fractures.

- For intermediate-sized fractures, blocks may be larger due to the potential for stair-case style blocks (partial blocks connected together due to terminating fractures); though the total volume of blocks formed will be less than when fractures are large.

- A mean fracture radius about 10 times the mean spacing can be considered continuous.

- When the mean fracture radius is less than 10 times the spacing, estimated block size is very sensitive and care should be taken to ensure biases are appropriately accounted for.

- Fracture size distribution had little impact on predicted block sizes; however, the variability and potential for large fractures had a significant impact on mean block sizes. A limited number of large fractures has a much greater effect than a large number of small fractures, thus it is more important to accurately characterize the proportion and extent of large fractures accurately while small fractures are of little consequence.

- When fractures are continuous (having a mean radius more than 10 times the spacing), the mean block size expected is about 1.6 times the mean spacing.
• Block size distribution curves show that the empirical block size estimates presented by Palmstrom (1996) and Cai et al. (2004) do not compare well to the size distributions generated in DFN analysis, particularly when fractures are small compared to spacing.

7.4.1 Future Work regarding impact of assumptions on model outputs
The models tested in this section all assumed 3 orthogonal sets with equal size and spacing parameters, as a simplified base case. To test the validity of the findings, more models using a wider range of input parameters should be analyzed, with particular attention to cases with more than 3 fracture sets, having different parameters for the different sets within a model, and with different variation ranges on distribution types.

Block size relative to excavation scale has been shown to control behavior on excavations where structurally controlled failures dominate (Bhasin and Hoeg, 1998). Developing a better estimate of the relationship between the mean block size, the scale of an excavation and the percentage of “intact” rock (or blocks larger than the excavation scale) might be of use in predicting failure modes and appropriate support measures in these conditions.

7.5 Findings using a practical example
A photogrammetric scan of a slope was analyzed to provide input parameters for DFN construction. Three different models were built from the scan, two using discontinuity surfaces detected semi-automatically and one using surfaces identified manually in a virtual mapping window. The findings are as follows:

• Automatically detected planes provide a reasonable range of orientation data when compared to manually selected data. It should be noted, however, that photogrammetric data identifies surfaces, not traces. Thus the usual sample bias guidelines are not relevant
as the orientations that should be selected most frequently (sets oriented normal to the sample plane) are those that this methodology is least likely to detect.

- Automatically detected surfaces tend to give shorter mean fracture size estimates as photogrammetry cannot incorporate traces into length estimates
- Manually selected surfaces, while better than automatically detected surfaces, are still limited in their extents and should be assumed to show fractures shorter than they are.
- Relationship between generated block sizes and empirical estimates is poor
- Predicted block size value from relationship presented in Chapter 5 is reasonably good
- Real data is likely to fall in the range identified in chapter 5 as non-continuous; mean fracture radius is likely to be within an order of magnitude of spacing. Thus care should be taken when deciding on appropriate spacing, mean size and size distribution parameters as small variations can have large impacts on model outcomes.

7.5.1 Future work using practical examples
Only a single site was tested here. Testing a wider range of sites with different characteristics would make conclusions here more robust. Different data collection methods, including conventional mapping, should be tested. Applying sampling techniques suggested by Zhang and Einstein (1998) and Rohrbaugh et al (2002). should also be carried out to compare results with conventional mapping.

Of particular interest may be to use subsequent scans of a slope where rockfalls have occurred, either naturally or controlled by scaling, to compare the volume of rock removed with the block sizes predicted by modeling.

7.6 General Conclusions
This thesis has examined some of the factors affecting the construction, generation and use of DFNs. Through evaluation of modeling parameters and assumptions, sample biases affecting
input parameters and potential uses of DFNs, some general guidelines and insight for developing DFNs for use in geomechanical practice have emerged. It is hoped that others seeking to construct and use DFNs for geomechanical purposes may use the findings from this work to aid in the decision making and analysis involved in DFN modelling.
Bibliography


