LINKING THE FRACTURE INTENSITY OF AN IN SITU ROCK MASS TO BLOCK CAVE MINE FRAGMENTATION

by

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Abstract

Prediction of cave fragmentation has been one of the biggest concerns for caving operation, since the inadequate assessment can potentially result in loss of project value and safety. The spatial variability of the natural fracture network holds significant implications with respect to block cave mine fragmentation. In this thesis, an in situ fragmentation model is generated, based on Discrete Fracture Network (DFN) models. The volumetric fracture intensity value ($P_{32}$), derived from the DFN model, is used as an indicator of the rock mass’ structural character, and it provides a direct link to rock mass fragmentation. Major structures were included in the model in a deterministic manner, and the spatial variability of the fracture intensity was analyzed to derive a geostatistical model of rock mass fragmentation. The fragmentation ‘block model’ was then superimposed onto a PCBC draw schedule model, in an attempt to link fragmentation and height of draw.

Poor data can potentially compromise DFN analysis, and may result in flawed validation and understanding. At the same time, it is important to define clear and objective methodologies, when analyzing field data, and when deriving input for DFN models. Piecewise Linear Interpolation and recreation of the conceptual DFN model are both used to study the influence of fracture intensity interval length and role of human uncertainty, on the final DFN-derived 3D spatial model. The results show that interval lengths are related to a resolution that can be effectively used in large-scale 3D continuum models, to represent the Representative Elementary Volume (REV) for the rock mass.
A digital image processing technique is applied in order to assess caved ore fragmentation. Validation of this method has been gained from the study of lab experiments. Furthermore, a conversion factor for relating 1D image-based measurement to 3D objects is calculated, since the DFN-based in situ fragmentation model yields volumetric size distribution, whereas image processing techniques yield equivalent spherical diameters. Finally, by using the above-mentioned input data analyses, this thesis investigates the possible links between natural fragmentation, secondary fragmentation, height of draw, and observed over-sized material and hang-up.
Lay Summary

Block caving is an underground mining method, that uses gravity to extract massive orebody located at depth. Mine schedule and operation can be heavily influenced by fluctuation in fragmentation size. This thesis focused on studying the influence of natural rock mass characterization on the unexpected fragments. The advent of the Discrete Fracture Network model, which can be defined by distributions of primary fracture properties, could provide a realistic description of rock mass. This study involved in-depth study of both Discrete Fracture Network properties and field measurement of fragmentation techniques. The model is compared against the actual operational data. From the analysis, it could be concluded that natural rock mass characteristics play an important role in block cave mine fragmentation. However, the influence of the natural rock mass diminishes, as the inter-particle breakage mechanism which occurs as the material travel towards the drawpoint (secondary fragmentation) intensifies.
Preface

This thesis is original and independent work, done by the author. The author was the lead author of the two published conference papers based on the work for this thesis. A co-author on all of these papers was the thesis supervisor.


The paper “A Piecewise Linear Interpolation Algorithm to Reduce the Uncertainty of Cumulative Fracture Intensity Plots for Discrete Fracture Network Modelling,” submitted in June 2015, and currently in the revision process, is based on Chapter 1.

In addition to these papers, the author was the second author for “Cave fragmentation in a cave-to-mill context at the New Afton Mine part I: fragmentation and hang-up frequency prediction,” published in Transactions of the Institution of Mining and Metallurgy, Section A: Mining Technology, July 2017. Working with the first author helped to develop alternative analysis methodologies, when comparing operational data with the model.
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<td>Aspect Ratio</td>
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<td>C31</td>
<td>The constants of proportionality</td>
</tr>
<tr>
<td>C32</td>
<td>The constants of proportionality</td>
</tr>
<tr>
<td>CFI</td>
<td>Cumulative Fracture Intensity</td>
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<td>DFN</td>
<td>Discrete Fracture Network</td>
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<td>FW</td>
<td>Foot Wall</td>
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<td>HOD</td>
<td>Height of Draw</td>
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<td>Hang-up</td>
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<td>Hanging Wall</td>
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<td>MRMR</td>
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<td>Fracture Intensity</td>
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<td>Fracture Intensity</td>
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<td>PLI</td>
<td>Piecewise Linear Interpolation</td>
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<td>REV</td>
<td>Representative Elementary Volume</td>
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<td>RMR</td>
<td>Rock Mass Rating</td>
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<td>RMSE</td>
<td>Root Mean Squared Error</td>
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<td>RSD</td>
<td>Relative Standard Deviation</td>
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<td>R-squared</td>
<td>Coefficient of Determinations</td>
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<tr>
<td>Sph</td>
<td>Sphericity</td>
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<td>Tpd</td>
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Acknowledgements

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I would like to acknowledge the Oyu Tolgoi Mine international scholarship for giving me the opportunity to pursue higher education in Canada.
Chapter 1: Introduction

1.1 Problem Statement

Soon after the extraction layout is established, and undercut is blasted, both oversized and fine caved material, drawn at drawpoint, bring the difficulty for the operation, including i) unavailability of drawpoints due to hangups; ii) blasting/secondary breakage costs; iii) early dilution entry and ore recovery; and iv) high risk of mud/water rush, due to fine migration. Therefore, the block cave mine design parameters are generally outlined by consulting expected cavability and fragmentation. However, frequently, the prediction of rock mass fragmentation still does not meet with actual fragmentation records.

An empirical rule-based model (Esterhuizen, 2005, Laubscher, 2000) and a numerical analysis (Cundall, Mukundakrishnan and Lorig, 2000; Castro, 2006, Rogers et al, 2010), have emerged to provide a quantitative characterization of the fragmentation model. Interestingly, none of the methods above can provide a realistic description of in situ rock mass, except DFN-based in situ and indirect primary fragmentation models (Elmo et al., 2008; Rogers et al., 2010). Furthermore, one of the biggest obstacles in modelling is due to the lack of direct access to the big scale rock mass; but, the characterization of rock mass can be subdivided into geotechnical units or domain, and might be potentially influencing rock breakage mechanisms. This is the practical need of building cave-scale in situ rock mass, which can be challenged by observed secondary fragmentation measurements.

In addition to the relevance of fragmentation to the previously discussed operational difficulty, the ability to predict cave fragmentation has the potential to become a valuable design and planning
tool, when it is integrated with a comminution circuit. Open-pit operations have been taking advantage of mine-to-mill models, and have done extensive work directed at integrating blasting with crushing/grinding, for the purpose of increasing overall productivity, and reducing energy consumption over the last 15-20 years (Stefan et al, 2016). A non-selective, mass mining method is largely relied upon for predicting the behavior of rock masses and the recovery of ore. However, an ore’s metallurgical characteristics and variation, is rarely applied to models, which quantify the NPV of the project. Furthermore, a potential link between accurate assessment of caved material fragmentation and its implication on mill performance, is not studied throughout. Starting in 2015, the Geomechanics Group and the Mine-to-Mill Groups at the University of British Columbia, are actively pursuing research on integrating cave mining with mill processes, a novel study envisaged to boost project value.

Cave-to-Mill’s group developed a database of underground caved ore’s size and hardness, from operational data, field study and laboratory test results, to derive a relationship between estimated in situ fragmentation in the DFN models and secondary fragmentation observed at the drawpoints. They did this by taking into account important parameters, such as the structural character of the rock mass, rock mass quality and fracturing mechanics within the ore column, drawpoints hang-up and secondary blasting. The in situ to secondary fragmentation relationship would then serve as an input for energy-benchmarking of the comminution circuit. Furthermore, the data will feed into the study of sensor-based ore sorting at a cave operation, and its impact on the size of the economic cave footprint.
To reach the Cave-to-Mill research objective, a six-stage milestone was developed, including:

1. Developing and standardizing the test procedure and method;
2. Visiting mine site, collecting and/or retrieving underground/surface sample, as well as operational data;
3. Conducting a lab experiment including lithology/alteration group classification, point load test, sieving and metallurgical test work;
4. Building preliminary DFN and developing sensor-based method (heterogeneity);
5. Updating DFN model and deriving relationship between in situ and secondary fragmentation; and
6. Performing final calibration and validation of fragmentation, and evaluating economic benefit of pre-concentration and cave-to-mill approach.

Over the last two years, two journal papers, two conference papers and two theses have been published, regarding the findings of Cave-to-Mill research (Munkhtsolmon et al., 2017; Stefan et al., 2016; Stefan et al., 2017; Liu et al., 2015; Elberel, 2017; Lui, 2016). The challenge for this thesis, was to complete stage 5, by building cave-scale DFN-based in situ rock mass block model, and to relate the model to operational data (hang-up events, secondary fragmentation measurements).

1.2 Research Objectives

From the mine site, both quantitative and qualitative discontinuity data can be collected, either from geological, or geotechnical logging. As the DFN-based approach offers the potential to maximize use of the data, cave scale DFN model proposed here will assist in the better
understanding of in situ rock mass, and its implications for fragments reported at drawpoint. The aim of this research is to develop a method to predict cave fragmentation size based on the volumetric fracture intensity of a rock mass. In order to achieve the objective, a number of secondary objectives must be addressed.

1. Increasing the confidence of the DFN input parameter, and finding alternative ways to tackle possible biases;
2. Increasing the confidence of image-based secondary fragmentation measurement, and finding alternative ways to tackle possible biases;
3. Building in situ rock mass fragmentation block model; and
4. Developing a methodology to compare an in situ block model to operational data.

1.3 Thesis Organization

This thesis is divided into 6 chapters: following this introduction (Chapter 1), are the literature review (Chapter 2), which will formulate a coherent research path, discussion on improving reliability of DFN input data and secondary fragmentation measurement (Chapter 3, 4), and discussion on methodology undertaken to build an in situ block model (Chapter 5). The final chapter presents a comparison of the model proposed here, with operational data, which is then followed by a conclusion and recommendations for further research. The organizational structure of the research chapters is shown in Figure 1.1.
Chapter 2
Literature review

Chapter 3
Novel Mathematical Algorithm to Mitigate Human Error and Scaling Effect of CFI plot for DFN modelling
Scaling effect Close-up view effect

Chapter 4
Volumetric Conversion And Shape Analysis Of Block Caving Mine Secondary Fragmentation Measurement
Processing secondary fragmentation measurement using image based method Post processing (volumetric conversion)

Chapter 5
Generating DFN Based In Situ Fragmentation Block Model
Pre-processing input data Conditioning borehole derived fracture intensity into volumetric fracture intensity using DFN code Geostatistical analysis and building block model Running cell mapping algorithm

Chapter 6
Comparison Between Secondary Fragmentation Measurement and In Situ Fragmentation Block Model
Pre-processing P32 value and hang-up event log Running PCBC monthly historic production scheduler to report HOD and corresponding average P32 values

Figure 1.1 Thesis structure, main research chapters
Chapter 2: Literature Review

2.1 Introduction to Block Caving Method

Block caving is classified as an unsupported underground mining method. Introduction of this method for iron ore mines can be traced back to the early 20th century in Northern Michigan, USA. This method is commonly referred to as mass mining, as its production rates are comparable to large open-pit mines. As large open-pit operations approach the end of their mine lives, block caving methods are increasingly becoming the method of choice for the mining industry, since they have the potential to yield extraction rates on a scale comparable to those of open-pit mining (e.g., in excess of 100,000 tonnes per day (tpd)); caving methods also allow for high efficiency and low production costs (Vyazmensky et al., 2010). Furthermore, as the operation is capable of transferring to full or partial automation, Tota (1997) once termed this method a “rock factory.”

Block caving may be used in massive or thick tabular orebodies, dipping fairly steep (>60°) (Brown, 2003). It is the most suitable underground method for low-grade disseminated orebody. The caving method largely relies on gravity to extract ore. The caving mechanism involves progressive fracturing, resulting from gravity and stress redistribution, initiated by the blasting of a horizontal panel, known as the undercut level (Vyazmensky et al., 2009). The undercut level feeds the production level, through bell-shaped ore passages called drawpoints. A general block caving mine layout is shown in Figure 2.1. As the ore is removed, the ore above continues to break and cave in due to gravity.
One of the critical parameters that determines the success of mass mining, is the size and shape of the plan area that is being caved. Two methods are used:

- Block caving, in which regular rectangular or square areas are undercut in a checkerboard pattern. Every block is drawn evenly, in order to maintain a near-horizontal plane of contact between broken ore and caved capping.
- Panel caving, in which ore in continuous strips is mined across the orebody. An inclined plane of contact between ore and capping is maintained during caving.

2.2 Fragmentation is a Challenge for Block Cave Mines

Considering the high upfront capital costs and the large degree of development and time lag before production reaches full capacity, this conceptually simple (use of gravity instead of explosives), but technically challenging, method requires detailed planning and reliable studies.
Block caving mines may have to consider a series of geotechnical issues. One of the big concerns surrounds managing rock mass fragmentation, since it plays a decisive role in the success of the mine operation (Moss, 2011). Furthermore, the design of the mine layout depends heavily on the cavability of the orebody (Brown, 2003). For example, drawpoint opening is defined to be three to six times larger than the maximum dimension of the ore fragments (Otuonye, 2000). The size of the ore at drawpoint can heavily affect downstream processes, including extraction, comminution processes and transportation (Gustafson et al., 2016).

In parallel, unexpected fragmentation at any stage of the cave operation is prone to significantly impacting draw schedules. More specifically, a problem that can affect draw schedules are large boulders/muck that plug drawpoints. These “hang-up” is commonly removed by using secondary blasting or secondary breakage (high-pressure water jet). Some operating mines (e.g., Palabora and DOZ/ESZ) have experienced high hang-up frequently (Dorador, 2016), which has adversely affected not only the availability of their drawpoints, but has also impacted the draw schedule, which has led to early dilution in terms of asymmetric drawing. Conversely, fine migration can also be a major issue for operations and safety.

2.3 Fragmentation and Mixing models

Currently, both the scale of the problem and the lack of direct access to the rock mass at project evaluation and design stages, makes the characterization and accurate prediction of rock mass fragmentation a very difficult task. In this context, caving geomechanics is still largely an
empirically-based discipline (Vyazmenzky et al., 2010). Fragmentation can be characterized in terms of (Brown, 2003) (Figure 2.2),

i) In situ fragmentation (blocks naturally present within the rock mass, before any mining activity takes place);

ii) Primary fragmentation (blocks that detach from the cave back as caving is initiated due to generation of new stress-induced fractures) and,

iii) Secondary fragmentation (blocks that form as the rock material falls onto the muckpile of caved material, and moves down through the ore column to the drawpoints).

Figure 2.2 Schematics of natural, primary and secondary fragmentation. Modified from Elmo et al., (2014).
To a great extent, in situ rock mass can be explained by open or weakly-closed structures, which are formed by the spacing, persistence and interconnectivity (Dorador, 2016; Jakubec, 2014). The caving process resulted in a high stresses redistribution, which triggers existing fractures to extend, and create new fractures. It potentially impacts upon primary fragmentation and requirement of secondary breakage (Moss, Diachenko and Townsend, 2006).

Study of veined rock masses has recently been of interest to a number of research and engineering practitioners (Jakubek, 2013; Kaiser, Amann and Bewick, 2015; Turichshev and Hadjigeorgiou, 2015; Bewick and Kaiser, 2016). Bewick and Kaiser (2016) have accentuated the role of veins on fragmentation. With the presence of veins, rock mass tends to look blockier from both core and blasted headings. Apart from the deceiving appearance, the vein has an implication on decreasing the strength of jointed rock block, as well as on the development of secondary fragmentation. The authors suggest open joints play an important role in primary fragmentation, while the tensile strength of veins and vein infilling potentially impact upon secondary fragmentation. Also, the intensity of weak veins’ $P_{10}$ and $P_{32}$ (this term will be explained more broadly in section 2.4) (Brzovic and Herrara, 2011) have been considered one of the important geotechnical parameters and geological structures, which needs to be incorporated in comprehensive analysis, apart from the geotechnical analysis of block model parameters of interest, rock mass rating (Bieniawski, 1976) and main geological structure (Miranda et al., 2016)

Secondary fragmentation is termed as rock decomposition that occurs as it moves along the draw column (Laubscher, 2000), and comminution in the column (Jakubec, 2014). Wimmer et al. (2008) has observed the analogy of secondary fragmentation to autogeneous grinding, because they
detected a flattening effect from mid-sizes of the Kiruna sub-level caving mine, which may also be due to “selective breakage” behavior, which was comparable to the shape of fragment size distributions typically attributable to autogeneous grinding, where self-breakage of large fragments grinds mid-fractions to fine (Lynch, 1977; Hahne et al., 2003). They assumed the mechanism of selective breakage might reduce fraction of medium size, but still leave strong, large boulders which are termed “hang-up”. Oversized material is a boulder that a load hauling and dumper (LHD) cannot handle. In case of New Afton Mine, rock is considered oversized if it is greater than 2 cubic meters (Bergen et al., 2009). According to New Afton Mine Geotechnical Report (Burgio, 2012), hang-up is termed as combination of rocks being able to bridge across the drawbell which is assumed to be 4.6m wide towards the base of the throat of the drawpoint. However, DOZ mine developed a drawpoint rating system, which was based on coarseness of ore, and its implication on reliability and availability of drawpoint (Kurniawan and Setyoko, 2008).

The number of parameters and zones of distinguished stress states (Pierce, 2009) have an important implication for secondary fragmentation, which is obviously a complex phenomenon. Wimmer et al. (2008) highlighted self-breakage, abrasion, crushing under superimposed load and fracturing of larger blocks under different forms of load, as key mechanisms (Wimmer et al., 2008). More recently, Dorador (2016) incorporated the effect of individual block, draw column, caving operation, rock fall impact, fine migration and cushioning into his model.

As the secondary breakage mechanism becomes effective in higher flow paths, a draw rate and fraction of the fine material are directly increased according to observations of ore processing characteristics of Kiruna mine (Lichter, 2007; Hahne et al., 2003). Similarly, lower draw rates
usually occur in primary fragmentation for DOZ mine, while higher draw rates attained a high draw column (Kurniawan and Setyoko, 2008).

The use of modelling approaches provides an opportunity to investigate the factors governing caving fragmentation, and to develop improved methodologies for the prediction of in situ fragmentation and secondary fragmentation. Furthermore, flow and mixing mechanism plays a major role for higher flow paths when the fragmentation is driven by secondary fragmentation. From the literature, a number of different models could be used to provide estimates of fragmentation sizes. Block caving fragmentation software (BCF, Esterhuizen, 1999) can be considered to be ‘accepted industry practice.’ Also, DFN combined ruled based primary and secondary model has emerged from advancement of modeling natural fracture network and hybrid Finite/Discrete Element codes (Rogers et al., 2010). Furthermore, some of the current approaches for describing mixing include: field marker monitoring (Brunton et al., 2016; Campbell, 2015; Wimmer et al. 2015), laboratory full-scale experiment (Power, 2004)) and numerical techniques, such as discrete-element Particle Flow Code (PFC) (Pierce et al. (2007) and REBOP (Cundall et al., 2000 - Itasca Consulting). However, it is noteworthy that there is no ubiquitously accepted consensus about which of the methods above should be used for assessing fragmentation and simulating flow, and each of those method requires further development.

Since the actual in situ rock mass is unknown, a series of decision trees developed in the BCF program, using available information of mining blocks, which includes the cave face orientation, stress, mining rock mass rating (Laubscher’s MRMR, 2000), joint set orientation, and joint set spacing (Castro et al., 2016). BCF can generate estimates of size distribution for in situ, primary
and secondary fragmentation. The empirical assessment took an account of block splitting, comminution and grinding of the blocks within the draw column, stresses at the cave back and their impact on secondary fragmentation size distribution (Wellman et al., 2012). However, the BCF program was reported to yield conservative results, and for the coarser size in particular (Ngidi and Pretorius, 2011, Dorador, 2016).

The REBOP software is based on the empirical breakage rules (Pierce, 2004), developed and determined in PFC3D (Itasca, 2005) simulations and confirmed by full scale physical model tests performed at JKMRC (Power, 2004) and calibrated at various mine sites, such as Henderson, Northparkes, Palabora and Cullinan (Pierce, 2004). In comparison to gravity flow simulation packages which uses fixed draw cone shapes (PCBC software of Diering, 2000), the shape of geometry in REBOP evolves as the rules are applied in time-step fashion which imitates extraction of ore from drawpoint (van As, 2000). However, it should be noted that a recent flow marker experiment had results which significantly deviated from the conventional ellipsoid flow theory (REBOP, PCBC and cellular automata) (Brunton et al., 2016). The effect of segregation, and thus preferential flow of certain fractions, could help to explain the observation made. It, therefore, has been confirmed that height of draw estimates of conventional ellipsoid models should be considered as an approximation, and require further investigation.

Rogers, Elmo, Webb and Catalan (2010) proposed an integrated modelling approach that combines Discrete Fracture Network (DFN)-related techniques, with a numerical hybrid finite/discrete code (ELFEN, Rockfield Software, 2010) to assess in situ, primary and secondary fragmentation. This
approach integrates geomechanically-derived rules in ELFEN, with the DFN code, FracMan (Golder Associates, 2009; Dershowitz et al., 1998).

Use of DFN in quantifying fragmentation and measuring the effects of hydraulic and explosives fractures has been spreading in mine practice quickly. There are a number of case studies published in literature. In the case of Sur Andes Pipa mine sector, within the Codelco’s El Teniente mine, Chile, to evaluate the impact of the differing pre-conditioning strategies on rock mass fragmentation, 3D blocks within representative volume of the pre-conditioned area have been mapped in FracMan. To differentiate effects of pre-conditioning strategies, 3D blocks (10m x 10m x 10m cubic rock mass), comprising a weaker vein with $P_{32}$ of 3.1, representing pre-conditioned strategies, are built into the code of FracMan. The effect of Hydraulic Fracturing (HF) in rock mass fracturing is preferred over Blasting Under Confined Conditions, considering a four times increase in fracture intensity $P_{32}$, the area of fracturing per (m2) per volume unit (m3). Also, a spatial distribution of low intensity ($P_{32}$) appears to correspond to location of extreme and large blocks (Brzovic et al., 2015).

A similar study was conducted in Codelco’s El Teniente mine, Chile. From the measurement campaign made from 1995 to 2014, the mine layout can be divided into three sectors (Hurtado and Brzovic, 2014). From sector one, predominantly mafic complex of hanging wall (HW) and foot wall (FW) as well as tonalite lithology is observed. From sector two, mafic complex of HW and FW, along with dacite is detected. Dacite lithology is measured from sector three (Hurtado and Brzovic, 2014). The different lithologies were assigned to varying $P_{32}$ values ranging from 2-15 (Brzovic et al., 2016) as shown in Figure 2.3. Thereafter, the competent massive rock mass with
few open discontinuities and a high frequency of veins is described by the geotechnical block model with 20 x 20 x 20 m$^3$ blocks (Brzovic et al., 2016). From the operational data, a large $P_{32}$ value for weak veins, resulted in better fragmentation (Brzovic et al., 2016).

![Image](image.png)

**Figure 2.3 Distribution of the $P_{32}$ values, level 1990 (modified from Millan Brzovic and Sequel, 2015)**

In case of Cadia East Panel Cave Mine, Australia, DFN modelling is applied to represent rock mass heterogeneity from $P_{32}$ variation in cave volume. Borehole fracture intensity clustered, based on the zones of similar intensity, and subsequently corrected for orientation bias. The intensity value is a converted $P_{32}$ value and is geostatistically modelled. The geostatistical in situ rock mass block model is integrated with ELFEN derived rules (Rogers et al., 2010).
2.4 DFN Based In Situ Fragmentation Model

A critical element for any caving project, pre-caving assessment is determining the likely distribution of the in situ rock mass fragmentation (Elmo et al., 2014). Generally, the question of assessing fragmentation comes down to finding a possible link between input (in situ fragmentation) and output (secondary fragmentation). A realistic description of the in situ fragmentation can be represented by tools such as DFN models (Elmo et al., 2008; Rogers et al., 2014). DFN is method of representing natural fracture network geometrically, and is based on statistical distribution of fracture properties. Also, the method offers an opportunity to maximise the use of fracture data collected from the logs of boreholes and mapping of rock exposures, especially during the project evaluation stage, when limited data are available. Using a DFN tool, more accurate geometric models of in situ fracturing can be developed, and the results can be used as a stand-alone, or an integrated tool, as a part of advanced geomechanical simulations (Rogers et al., 2014; Elmo et al., 2014). One application of interest is the assessment of rock mass fragmentation for block and panel cave operations (Elmo et al., 2008; Rogers et al., 2014; Elmo et al., 2015). However, there are some consideration should be taken into account is reliability of data and data processing procedure which will be discussed in more detail in Chapter 3. The following input parameters are generally required to generate a relatively simple DFN model (Elmo et al., 2016):

i) Fracture spatial model;

ii) Fracture intensity;

iii) Fracture orientation;

iv) Fracture size; and

v) Fracture termination.
2.4.1 Fracture Spatial Model

Three predominant spatial models could be adopted, to generate a DFN model (Elmo et al., 2014). In the Enhanced Baecher model, fracture location may be defined by a regular (deterministic) pattern or by a stochastic process. The stochastic approach assumes that the fracture centres are randomly located in space using a Poisson process. The Nearest-Neighbour model is particularly well-suited to fractures that are clustered around major points and faults, by preferentially producing new fractures in the proximity of earlier fractures (Dershowitz et al., 1988). The Levy-Lee model is a fractal model; its key features are that fracture centres are created sequentially, and that the size of a fracture is related to its distance from previous fractures (Staub et al., 2002).

2.4.2 Fracture Intensity

A unified system of fracture intensity measures, introduced by Dershowitz & Herda (1992), helps to differentiate scales and dimensions. The notation \( P_{ij} \) (Table 2.1) is adopted wherein the subscript \( i \) denotes the dimension of the sample, and the subscript \( j \) denotes the dimension of measurement; accordingly, there are 3 distinct, yet interconnected fracture intensity parameters: 1D linear intensity (\( P_{10}, m^{-1} \)), 2D areal intensity (\( P_{21}, m/m^2 \), defined as ratio of total fracture length to unit area) and 3D volumetric intensity (\( P_{32}, m^2/m^3 \), defined as ratio of total fracture area to unit volume).

Note that \( P_{10} \) and \( P_{21} \) data are directionally biased with respect to orientation of boreholes/scanlines in relation to the orientation of fractures, while the volumetric fracture intensity \( P_{32} \) can indirectly refer to orientation and size distribution of rock blocks in the sense that the \( P_{32} \) value is highly sensitive to distinct fracture orientation and size distribution. Those are the underlying reasons...
why $P_{32}$ possesses greater value, and why it represents a true intensity indicator in the context of DFN modelling.

Table 2.1 Fracture intensity $P_{ij}$ system (modified from FracMan Manual, Golder, 2016)

<table>
<thead>
<tr>
<th>Dimension of Feature</th>
<th>Number of Fractures</th>
<th>Fracture Trace Length</th>
<th>Fracture Area</th>
<th>Fracture Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

- Objective Measures
- Linear Measures
- Areal Measures
- Volumetric Measures

### 2.4.3 Fracture Orientation

There are two approaches for defining fracture sets. A disaggregate approach refers to generation of distinct fracture sets which later combined to represent overall nature of fracture network. Fisher, Bingham, Bivariate Fisher and Bivariate Bingham distributions commonly fit into fracture sets to represent fracture orientation. The Bivariate Bingham is the slowest for fracture generation and the Fisher distribution has particularly convenient mathematical properties. When field data does not conform with any of those distribution, for example in case of a highly dispersed scatter, pseudo-replicate sample which is derived from multiple random sampling from the original sample is an alternative method. It is termed as bootstrapping approach (Rogers et al., 2007).
2.4.4 Fracture Size

From the exposed rock faces, fracture shape and sizes can be quantified using analytical methods (Zhang and Einstein, 1998; Mauldon, 1998) based on assumption that i) fractures are planar, and ii) fractures are assumed to be polygons with n sides. Size of the polygons is defined from a radius of a circle of equivalent area. Fracture/fault trace length are not equal to fracture radius. The fracture length always refers to geological surface or mining exposures; however, the fracture radius indicates radius of a circle, or the radius of a polygonal fracture with equivalent area to a circle. Therefore, DFN model requires pre-processing such as analytical conversion method when dealing with field data.

2.4.5 Fracture Termination

Structural character of rock mass in terms of interconnection of fracture sets can be defined using fracture termination percentage. Also, termination type is important in explaining chronology of fracture formation. For example, T-type of termination can explain in what order fracture sets has formed (Elmo, 2014) (Figure 2.4).

![Figure 2.4 Type of termination](image-url)
2.5 Size Distribution of In Situ Rock Mass

A cell mapping algorithm is capable of generating volumetric distribution out of the DFN models (Elmo et al., 2010). A cell mapping algorithm is used to provide an initial estimate of the rock’s natural fragmentation (Figure 2.5).

Firstly, all the fracture intersections are found from the specified grid elements (2). Then, collection of grid faces and connection information is stored (3), which is then used to build a Rock Block of contiguous grid cells (Elmo et al., 2010).

Figure 2.5 FracMan DFN-based cell mapping algorithm (Source Elmo et al., 2014)
2.6 Image Based Method for Assessing Secondary Fragmentation

Secondary fragmentation is an outcome of caving mechanisms, and acts as an input for downstream processes (secondary blasting effort, if required, haulage and comminution process). Also, the main observation that can be used for calibrating in situ fragmentation, are secondary fragmentation which is visible at the drawpoints at extraction level (Wellman et al., 2012). Furthermore, Wimmer et al. (2008) has named that one of the two main strategies to study the effect of secondary fragmentation, which is difficult to verify, can be determining by shape and surface property of fine particles; the property can define if the caved ore is exposed to autogenous grinding (Forssberg and Zhai, 1985).

The caved material can potentially be measured by means of direct physical methods or image processing techniques. The most accurate methods, which are physical methods, mainly refer to screening; however, it is neither practical to take a representative sample from a drawpoint, nor to include mass and size of hang-up causing boulders within the muckpile, as the particles are not accessible for sieving (Lui et al., 2015).

Image-based techniques are computer based photograph processing tools that originated in the 1980s with the purpose of measuring blast fragmentation. The emergence of the automatic edge detection algorithm has accelerated both processing time and accuracy of results. The digital image-processing tool offers the following advantages over physical methods: it is faster and more convenient than traditional approaches, does not interrupt normal production, and is not limited by the size or weight of rock.
In the light of integrating cave to mill, there is a need to acquire greater confidence on the secondary fragmentation measurement, as it is a key parameter for both cave and mill. Also, as Wimmer mentioned, there could be a possible link between fragmentation and properties of particles. However, the accuracy of the measurement of fragmented material at drawpoint has been documented rarely in the literature. From the previous study of Cave-to-Mill research, the output of the WipFrag software for measuring caved muck showed good agreement with manually sieved size distribution, when the edge was delineated manually (Liu et al., 2015, Nadolski et al., 2015). When it comes to comparing results from WipFrag, which is the equivalent sphere diameter, to DFN-derived in situ fragmentation measurement, which is cubic meters, the dimensions cannot directly be converted. Chapter 3 introduces a lab experiment conducted to convert 2D image to 3D volumetric measures. Moreover, based on measured shape and size of caved material, linkage between caved material’s size and shape is analyzed to provide useful insight on accurately determining size distribution using the image-based method.
Chapter 3: Reduce the Uncertainty of Cumulative Fracture Intensity Plots for Discrete Fracture Network Modelling

3.1 Introduction

The block size distributions for 3D DFN models can be estimated using a grid-cell approach, known as Implicit Fragmentation Grid Algorithm (mentioned in literature review). However, prior to any immediate assessment, building reliable mine-scale DFN models, that incorporate the influence of deterministic features within the stochastic rock mass fabric, is crucial (Elmo et al., 2014; Elmo et al., 2016). For this purpose, geostatistical methods can be used to interpolate grid-based properties throughout the assumed cave volume (Rogers et al., 2014) and to develop a mine scale model to predict cave fragmentation.

Concerning the importance of adhering to guidelines for data collection, data uncertainty in the context of building DFN models has been addressed by Elmo et al. (2014). Typical DFN input parameters include: fracture intensity, fracture orientation and fracture size; these can be estimated based on available geotechnical data. Fracture orientation and fracture size distributions are defined in this study, according to the general guidelines for DFN modelling for geotechnical applications, discussed in Elmo et al. (2014), as well as Elmo et al. (2015).

\( P_{32} \) can be calculated by establishing a linear relationship between measured \( P_{10} \) and \( P_{21} \) intensities and simulated \( P_{32} \) intensity. The constants of proportionality, \( C_{31} \) and \( C_{32} \), depend on the relative orientation of the fractures, to the orientation of the sampling panel or scanline/borehole, and the fracture radius distribution. Alternatively, a DFN model could be generated by conditioning the
DFN model, to a direct replication of the number of fractures intersected along a scanline/borehole. This process is known as $P_{10}$ conditioning.

To account for directional bias, $P_{10}$ intensity properties can be converted to a non-directional $P_{32}$ potential property, using the method proposed by Wang (2006). In this study, a $P_{10}$ conditioning approach is used to estimate volumetric $P_{32}$ measurements. $P_{10}$ values are assessed, based on borehole data, and then, specific intervals are selected for $P_{10}$, since linear fracture intensity may vary quite considerably. The most effective way of identifying rock mass, where the average degree of fracturing remains constant over considerable depth, is by using cumulative fracture intensity (CFI) plots. In the literature, an interval length sufficient to achieve a good modelling resolution, is in the range of 10-100m (Elmo et al., 2014; Elmo et al., 2015; Rogers et al., 2014). Before selecting an appropriate interval length to define $P_{10}$, it is important to highlight what interval length may potentially oversimplify the characteristics of rock mass, by averaging fracture intensity; in contrast, selecting a very small interval might yield overly refined results, where the true structural character of the rock mass in the DFN model might be misrepresented. In particular, this study has focused on introducing a more objective method to define appropriate interval lengths for $P_{10}$ calculations.

3.2 Piecewise Linear Interpolation in CFI Plot

The objective of finding different zones of rock mass quality (based on linear intensity) from CFI plots, can be fulfilled to an acceptable level of accuracy, by using a Piecewise Linear Interpolation (PLI) algorithm, which provides a better mathematical approximation, independent of human error and scale effects. The algorithm can identify zones based on selected constant intervals, and
adaptable altering intervals, which follow the curvature of the scatter. For example, if we connect
the dominant points \((x_1, y_1), \ldots, (x_n, y_n)\) of \(x(1:n)\) and \(y(1:n)\) data, a piecewise linear function can
be visually described, and this function is built upon the local linear interpolants given by,

\[
L(z) = \begin{cases} 
L_1(z) = a_1 + b_1(z - x_1) & \text{if } x_1 \leq z < x_2 \\
\vdots & \vdots \\
L_{n-1}(z) = a_{n-1} + b_{n-1}(z - x_{n-1}) & \text{if } x_{n-1} \leq z < x_n 
\end{cases} \tag{3.1}
\]

where the coefficients are defined by,

\[
a_{n-1} = y_{n-1} \quad \text{and} \quad b_i = \frac{y_n - y_{n-1}}{x_n - x_{n-1}} \tag{3.2}
\]

Assigning values at selected constant intervals, can be done using linear interpolation. Also, by
using a recursive partitioning algorithm that discovers extra nonlinear sections, the scatter can be
approximated more accurately, by setting two conditions for subintervals, \([x_L, x_R]\), which is
formulated as follows (Bindel, 2012; Bartels et al., 1987; De Boor., 1978):

\[
\left| f \left( \frac{x_L + x_R}{2} \right) - \frac{f(x_L) + f(x_R)}{2} \right| \leq \delta \tag{3.3}
\]

\[
x_R - x_L \leq h_{\text{min}} \tag{3.4}
\]

where \(\delta\) is a given positive tolerance, and \(h_{\text{min}}\) is the length of an acceptable subinterval. The first
condition measures discrepancy between \((x_L, f(x_L))\) and \((x_R, f(x_R))\) and \(f(x)\) at the interval
midpoint \(m = (x_L + x_R)/2\), assuming \(f\) has two continuous derivatives. The second condition
pointed out the acceptable short subinterval. Figure 3.1. shows an example of adaptive altering
intervals in a 250m deep borehole.
3.3 DFN Model Specification and Analysis

A conceptual DFN model was generated using the code FracMan (Golder, 2016; Dershowitz et al., 1988), using field data from an undisclosed mine, which can be seen in Table 3.1. The DFN model was generated within a selected box region, that provides appropriate modelling resolution. In order to take the issues concerning statistically significant difference into consideration, a number of Monte Carlo realizations were made for each analysis.

<table>
<thead>
<tr>
<th>Data type</th>
<th>Data source</th>
<th>DFN model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial analysis</td>
<td>-</td>
<td>Enhanced Baecher</td>
</tr>
<tr>
<td>Orientation</td>
<td>2D mapping on drift exposures</td>
<td>Bootstrap method</td>
</tr>
<tr>
<td></td>
<td>1D geological oriented borehole</td>
<td></td>
</tr>
<tr>
<td>Intensity</td>
<td>Assumed P32 values</td>
<td>Volumetric Fracture frequency</td>
</tr>
<tr>
<td>Length</td>
<td>2D mapping on drift exposures</td>
<td>Log-Normal mean 2m, standard deviation 2m</td>
</tr>
<tr>
<td>Termination</td>
<td>-</td>
<td>No field data available</td>
</tr>
</tbody>
</table>
3.3.1 Analysis Step 1

The first step was to convert $P_{10}$ intensity into $P_{32}$. The $P_{10}$ conditioning method helps with dealing with the directional bias imposed by the relative orientation of the fractures and the orientation of the borehole. The simulation considered a $10\text{m} \times 10\text{m} \times 10\text{m}$ box, which is the same size used for the grid block for the subsequent fragmentation analysis. The analysis is carried out as follows:

- A DFN model is generated, using selected parameters for fracture orientation and length, within the defined box region;
- A simulated borehole is used to find the intersecting fractures, and to calculate a simulated $P_{10}$; and
- The analysis is repeated 20 times for every assumed fracture intensity, $P_{32}$ (1, 3, 5, 7 and 9), and a linear relationship between simulated $P_{32}$ and $P_{10}$ is established (Munkhchuluun, 2017).

As shown in Figure 3.2, the constant of proportionality ($C_{31}$) is approximately 1.66; this value is then used for Step 2 of the analysis. Note that the conversion factor will vary, depending on fracture properties and orientation of the borehole.
3.3.2 Analysis Step 2

The second step in the analysis looks at the influence of the selected interval length, on $P_{32}$ measurements. A much larger box region, with dimensions of 200m x 200m x 200m, is chosen to represent a much larger rock mass, as seen in Figure 3.3. Four volumetric fracture intensities ($P_{32}$ - 1, 3, 5 and 10) are assumed, and 5 DFN realizations are generated for each of those. The average of the 5 iterations is used for the final comparison. Using the intersecting fractures down the borehole, CFI plots with customized interval lengths are plotted according to two scenarios: first, constant interval lengths of 10m, 20m, 30m and 40m, and second, using an adaptive altering interval.
Realistic comparisons can be made, if we compare the CFI plot-derived $P_{32}$, with the initial overall $P_{32}$, used for generating fractures. The CFI plot can be simply translated into a $P_{10}$ value. Coupled with $C_{31}$, the $P_{10}$ value can be transformed into a $P_{32}$ value.

![Figure 3.3 Example of generated DFN model representing a large rock mass ($P_{32}$ equal to 1)](image)

Volumetric fracture intensity equal to five, is chosen as an example in “Scenario 1.” Constant interval lengths of 10m, 20m, 30m and 40m are compared to each other in a $P_{32}$ histogram, as shown in Figure 3.4. The peak of the distribution is in range of [4.1, 4.65]. Longer tails generally occur when using shorter $P_{10}$ intervals, whereas a more distinct peak is observed when using longer intervals. The percent deviation of average $P_{32}$ values of the 4 different intervals are estimated to be 1.2%. Similar characteristics are observed from other $P_{32}$ values at other intervals (1, 3 and 10). It is noteworthy that percent deviations of $P_{32}$ values of 5 Monte Carlo simulations, decreased as the $P_{32}$ increased (Table 3.2 below).
An adaptive altering approach to select fracture intervals is compared to a 10m constant interval in “Scenario 2.” The recursive partitioning algorithm is applied in the PLI, with a threshold to acquire a similar number of intervals as the constant 10m interval CFI plot generates. Initial input $P_{32}$ values for simulations was equal to 5 for both analyses (Figure 3.5.). The adaptive altering interval results in highly distributed $P_{32}$s, compared to $P_{32}$s derived from constant 10m intervals. Even though any deterministic features, such as fault, were not included in the simulation, some intervals were indicating considerably high $P_{32}$ values (equal to 8-10), as a very persistent local feature. However, it should be noted that the case above is likely to correspond to small intervals. Like “Scenario 1,” the average values of the two distinct partitioning approaches were identical, as shown in Table 3.3.

<table>
<thead>
<tr>
<th>$P_{32}$</th>
<th>Percent deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>32%</td>
</tr>
<tr>
<td>3</td>
<td>23%</td>
</tr>
<tr>
<td>5</td>
<td>17%</td>
</tr>
<tr>
<td>10</td>
<td>15%</td>
</tr>
</tbody>
</table>

Figure 3.4 $P_{32}$ histogram of different constant intervals 10m, 20m and 30m in well 4 ($P_{32}$=5)
The true persistent feature must always be found from the borehole, and modelled separately. The adaptive altering interval in the application of building block models might be detrimental, in that it would have biased the final results, because the significant high value (or low value) should not take part in the interpolation process for latter analysis. However, the PLI is considered to be pushing the concept forward, by generating highly accurate approximation, and disclosing the true nature of conceptual models. The model should fit for the purpose; in other words, the model should be driven by its objective. Therefore, the constant 10m interval is considered useful for geostatistical analysis. Evidently, there is no point in aiming toward details or oversimplification.

### 3.3.3 Analysis Step 3

This step is used to define any relationship between borehole spacings, for the purpose of building a geostatistical block model. Also, the analysis will serve as validation for PLI algorithm. In this analysis, four and eight boreholes, placed evenly spaced from each other, in a box region of 200m x 200m x 200m. Subsequent to assigning a $P_{32}$ value and generating DFN, which was produced in Steps 1 and 2, an interpolation process is used to recreate a DFN-derived fragmentation block.
model for a 10m x 10m x 10m region. Parameters of the interpolation can be found from Chapter 5, section 5.3. The following key points characterise Analysis Step 3:

- Potential bimodalism and outliers are determined from boreholes’ P32 histogram;
- Composites are created to convert the boreholes’ division into a standardized length;
- Understanding of likely orientation of greatest continuity, is inferred from orientation of fractures intersecting with simulated boreholes. The final direction of anisotropy is analyzed by comparing number of variogram maps with different orientations; and
- P32 value is distributed throughout the block model, using ordinary kriging, as shown in Figure 3.6.

As the initial P32 value increases, the difference between the recreated P32 value and overall P32 value, increases as well, as presented clearly in Table 3.4. This might be due to the characteristic that a higher P32 value is less sensitive to persistence factor (Elmo et al., 2014; Elmo et al., 2008). Regardless of this deviating trend, the recreated DFN implicated model indicate that linear fracture intensity (P10) found from PLI algorithm is a potential tool for represent initial true fracture intensity after the interpolation process.

![Figure 3.6 P32=5 block model using constant 10m partitioning](image)

<table>
<thead>
<tr>
<th>Borehole</th>
<th>Initial P32</th>
<th>Recreated P32</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 Borehole</td>
<td>0.84</td>
<td>2.57</td>
</tr>
<tr>
<td>8 Borehole</td>
<td>0.84</td>
<td>2.58</td>
</tr>
<tr>
<td>Difference</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Average difference</td>
<td>0.01</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.4 Interpolation bias on more scattered boreholes
The interpolation was biased with more scattered boreholes; however, the difference was subtle. The average difference between recreated and initial DFN was equal to 0.01 by P32 convention. To quantify impact of the 0.01 difference, a cell mapping algorithm is implemented in both a P32 value equal to 1, and a P32 value equal to 0.99, to provide an estimate of in situ fragmentation block size (Figure 3.7. below). The 0.01 change in P32 was corresponding to 1.05 times reduction, in fifty percent passing (30.1m$^3$ reduced to 28.6m$^3$), which is not a significant difference. Note that the resulting particle size distribution (PSD) curve will vary, depending on the P32 value. P32 values equal to 1 and 0.99 were chosen as an example. Also, the in situ fragmentation is cut off at 8m$^3$ which is due to computational requirements in the number of cells (100 x 100 x 100) in the DFN model. Based on these results, a 50m spacing between boreholes could yield acceptable fragmentation results.

Figure 3.7 Particle size distribution (PSD) of P32-0.99 and P32-1
3.3.4 Analysis Step 4

The final step looks into the potential human uncertainty factor when analyzing CFI plots. If a $P_{10}$ interval is manually selected from the CFI plots, without using the same maximum depth scale for all boreholes, there is a risk of users picking up very short and unrepresentative intervals. An example is shown in Figure 3.8, where two CFI plots with different maximum depth values result in perceived (very short) representative intervals, that are actually just the result of a “close-up” view. The “close-up” effects clearly reflect human uncertainty (different users, using different scales, may not see the same intervals).

![Figure 3.8. Manually selected interval of 200m borehole vs. automatically selected interval of 50m borehole](image)

3.4 Concluding Remarks and Discussion

DFN modelling provides a practical solution for estimating cave mining fragmentation. However, data processing methodologies must be clear and objectively-driven; hence, the human uncertainty and potential sampling bias can be reduced. This study has looked into CFI plots and objective methods, to define interval lengths for $P_{10}$ estimation. It is recommended that the minimum interval...
length should be equal to or larger than, the grid resolution used for fragmentation analysis. Other key findings include:

- As the interval length defined by the CFI plots increases, the $P_{32}$ distribution shows a more distinct peak. In contrast, smaller interval lengths resulted in evenly distributed $P_{32}$ values. However, the averages of different intervals were still similar;

- Using a PLI recursive partitioning algorithm generates highly accurate and objective estimation of fracture intervals. It indicated that the DFN simulation on a large rock mass, might result in highly variable $P_{32}$s at the local level, due to the random nature of the simulation. Some intervals show fault zone characterization, regardless of how small their overall fracture intensity happened to be;

- In case of homogeneous rock mass, number of fractures intersecting with borehole is not varying considerable with respect to borehole spacing;

- Validation of PLI algorithm is done by recreating implicit block model from big scale DFN model;

- The difference between simulated $P_{32}$ values in the block model, and the inferred overall $P_{32}$ value for the rock mass, increased as the $P_{32}$ value increased; and

- Practitioners should be aware of the human uncertainty introduced in the analysis of CFI plots, by the so-called “close-up” effect (different users, using different scales may not see the same intervals).
Chapter 4: Volumetric Conversion and Shape Analysis of Block Caving Mine
Secondary Fragmentation Measurement

4.1 Introduction

The secondary fragmentation, which is visible in drawpoint, is an outcome of caving mechanisms, and an input for downstream processes (secondary blasting effort, if required, haulage and processing plant). However, the accuracy of the measurement of fragmented material at muck piles, has been documented rarely in the literature. In the scope of the cave-to-mill research group, photographs of secondary fragmentation at drawpoint are taken periodically, and used for final comparison with the simulated in situ rock mass.

Both sieving and image-based size determination, are not capable of yielding a size distribution in volume, whereas DFN reported volumetric estimates by convention. This Chapter initially focuses on the optimization of the shape factor for particles to convert WipFrag-derived particle size into actual volume, which is determined using the water displacement method. Therefore, the results of in situ and secondary fragmentation are potentially compared to each other. Afterward, emphasis is given to the interconnection between the shape and the size of particles.

4.2 Volume Optimization and Wipfrag Analysis

Images are taken periodically from the drawpoint of an undisclosed underground mine, to assess secondary fragmentation in scope of the cave-to-mill research program. The images were analyzed by WipFrag software (Nadolski et al., 2015), which is one of the frequently-employed packages for blast fragmentation measurement. Prior to taking images, airborne dust must have been kept to a minimum. Dual scale reference markers were placed in the upper and lower sections of the
muckpile, to correct the tilt of the slope relative to the camera angle. Also, two portable lights were arranged to minimize shadow effects. Based on sphericity, which is length to width ratio, and geometric probability, WipFrag code generates the nominal diameter of a spherical distribution of the muckpile (Norbert, 1996).

In practice, the evaluation of the particle size in the dimension of volume, is more challenging than in the dimension of length (Dosti and Bastiaan, 2011). Besides the accurate analysis, it is also crucial to translate output of the analysis into its specified purpose. For example, if fragmentation assessments were generated on the basis of corresponding aperture size, it is more applicable for mineral processing analysis to be used, whereas size distribution in volumetric is more relevant when defining the relationship between in situ and secondary fragmentation. Even though the output of WipFrag, a nominal diameter of sphere, can be converted into volume using the spherical volume equation with ease, a lab experiment was conducted to give greater confidence.

4.2.1 Experiment and Procedure

Two experiments were carried out on narrow distributions of 3 different media, with a mean relevant aperture size of 24mm, 50mm and 144mm. The first experiment is intended to take an image in a laboratory setting which was arranged to be similar to drawpoint, and then process it in the WipFrag software. In the model dimensions, the following are included: distance from the toe to camera, slope angle, dual reference and object, as shown in Figure 4.1. Furthermore, the camera took images from two different points: one is posed subparallel to the slope, and others are located sub-perpendicular to the slope, to identify orientation bias arisen from the tilt of rocks relative to the camera position.
Figure 4.1 Experiment-1 taking an image from drawpoint like setting

Procedure for taking images in a laboratory setting is listed below:

1. Place rock in the middle of the slope;
2. Take an image from two stations (subparallel and sub-perpendicular); and

From the second experiment, the volume of each rock was determined from the amount of water displaced after adding the particle of interest to a test tube filled with water. Next, each rock’s thickness, length and width, were measured according to the following steps (Sneed and Folk, 1958):
1. Find the longest length of the particle (Dx);
2. Project particle along the axis found in step 1, on the plane perpendicular to the axis found in step 1;
3. Find the longest length of the projection;
4. Projection along the axis found during step 3, on the plane perpendicular to the axis found in step 3; and
5. Find the longest length of the projection obtained in step 4.

Afterward, for each particle, the “true” particle mass was obtained by accurate weighing.

### 4.2.2 Methodology

The correlation between actual volume and volume of sphere which is estimated from WipFrag, was not satisfactory, as its Root Mean Square Error (RSME) can be seen in Table 4.1. Therefore, alternative shapes, rectangular prism are proposed to fit WipFrag results into actual volume, by optimizing shape factors of the shape. The calculation of shape factor in WipFrag is based on sphericity, which is simply length to width ratio of the material. However, Esterhuizen (2005) and Kalenchuk et al. (2006) suggested the characterization of block shapes, based on their developed aspect ratio (AR) equation, which is designated to relate the block shape to its ease of splitting, instead of a normal aspect ratio, which is longest to shortest dimensions of the block, as presented in Figure 4.2. The definition of shape factor is involved in the calibration analysis.
A simplified shape is considered for rectangular prism whereby thickness is equal to width because the simplified shape results in better fit with actual volume (Table 1). For a rectangular prism model:

\[ a = \text{\textit{d}}; \quad AR = \frac{A}{6V} \cdot a \quad \text{(Esterhuizen, 2005) \quad (4.1)} \]

\[ b = \frac{2 \cdot a}{3AR - 1} \quad \text{(4.2)} \]

Where \( A \) is the surface area of the block, \( V \) is the volume, \( a \) is the longest edge of the block, \( \text{\textit{d}} \) is equivalent diameter of sphere.

For the spherical model:

\[ a = \frac{\text{\textit{d}}}{2} \]

\[ V = \frac{4}{3} \cdot \pi \cdot a^3 \quad \text{(4.3)} \]

Both sphericity and AR is fitted sequentially, in order to minimize RSME between the actual volume and model volume. The coefficient of determinations (R squared) of two models were consistently high, whereas the RMSE were comparatively high for the spherical model. Also, it is
clearly shown the Figure 4.3, that the spherical model overestimates the real volume. One variable based (shape factor) and constraint free optimization process is flexible so that the best possible shape factor for rectangular prism yielded 34% RMSE to the actual volume. The optimized shape factor can be applied to after WipFrag analysis to provide volumetric distribution that can be compared to the outputs of a DFN model.

Table 4.1 Model versus actual volume

<table>
<thead>
<tr>
<th></th>
<th>Rectangular prism</th>
<th>Sphere</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shape factor</td>
<td>1.52 - Aspect Ratio</td>
<td>-</td>
</tr>
<tr>
<td>R squared</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>RMSE</td>
<td>34%</td>
<td>71%</td>
</tr>
</tbody>
</table>

![Figure 4.3 Comparison of simplified shape models](image-url)
4.3 Caved Material Shape Analysis

There is lot of known synergy between material characteristics. For example, particle size composition exerts a fundamental control over its mineralogy and geochemistry. Material \(< 2\mu m\) will be composed primarily of silicate minerals, whereas the larger size fractions will be dominated by quartz. (Walling et al., 2000). Likewise, questions arise if the particle size, which is an eminent component of material analysis, had any implication on its shape. The second analysis is attempted in order to define a link between caved material size, as well as its shape, and its implications on digital image processing tools.

Early mathematician Brunton (1895) proposed shape factor could predict particle mass from the sieve size and density (\(p\)) of the particle. He adopted a cubic shape for defining shape factor, which is the ratio of the volume of a cube, with the sieve size versus the actual volume of the particle. Later P. Gy included Brunton’s shape factor for his sampling theory under the assumption that a constant shape factor could be applied for all particles, by introducing Fundamental Sampling Error; therefore, an inadequately specified shape factor, has a potential to be a major source of the sampling uncertainty. Recently, to overcome this bias to some extent, Dosti and Bastiaan (2011) suggested the use of their proposed multi-axial particle shape factor (Equation 4.6), which takes a number of independent sizes of particle into account, rather than relying on only one size of particle, sieve size.

\[
m = \rho f_N \prod_{i=1}^{N} D_i^{3/N}
\]  

(4.4)

wherem = mass of the particle, \(\rho\) = density, \(N\) = multi-axial dimensionality, or number of dimensions, \(f_N\) multi-axial shape factor, \(D_i\) = the ith independent particle. Too low an \(N\) value
cannot describe shape of the sample completely, while too high an N value can be considered an irrelevant measurement that can distort description of particle shape. Dosti & Bastiaan (2011) has adopted N=3, which was deducted from method of Sneed and Folk (1958):

\[ m = \rho f_3 D_x D_y D_z \]  \hspace{1cm} (4.5)

Where \( D_x, D_y, \) and \( D_z \) are the three orthogonal axes of particles, as identified by Sneed and Folk. The three orthogonal axes, mass and volume of samples, are measured from experiment 2, so that \( f_3 \) of each individual rock can be determined using equation:

\[ f_3 = \frac{m}{\rho D_x D_y D_z} \]  \hspace{1cm} (4.6)

As mentioned in experiment and procedure, thickness, length and width measurements of the three-different media are used in this analysis. Note that number of samples might be non-representative for this analysis, and require more data for further sophisticated analysis. Average shape factor, \( f_3 \), of each size range were subsequently used to predict individual particle masses using Equation 4.6. Table 4.2 shows the Root Mean Squared Errors (RMSE) of each mass prediction. The error is reasonable because coffee bean, which is comparatively homogenous shaped material than fragmented rocks, were assigned to 9% RMSE from the actual mass (Dosti and Bastiaan 2011). Also, greater errors were observed from smaller particles.
There are 3 sources of error as described by Dosti and Bastiaan (2011), including either too low, or too high an N value, a non-representative number of samples, and inconsistency of shape factor. With an assumption that the larger error in small rocks is due to large shape variance, various shape factors are compared: Esterhuisen’s Aspect Ratio (2005) and WipFrag-based Sphericity, as shown in Table 4.3.

<table>
<thead>
<tr>
<th>Mean relevant aperture size, mm</th>
<th>( f_3 – ) shape factor</th>
<th>Number of Samples</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>24</td>
<td>0.72</td>
<td>68</td>
<td>31.7</td>
</tr>
<tr>
<td>50</td>
<td>0.65</td>
<td>30</td>
<td>27.9</td>
</tr>
<tr>
<td>144</td>
<td>0.16</td>
<td>10</td>
<td>27.2</td>
</tr>
</tbody>
</table>

There was a tendency for variance of aspect ratio (Esterhuisen, 2005) to increase with decreasing size, whereas lower variance was corresponding to bigger particles. Mass prediction analysis suggests the same trend. Also, it is worth noting that more irregular shapes (AR-1.7) were observed from smaller particles. However, there is a notable discrepant trend observed from sphericity. The relative standard deviation (RSD) increased up to 23% for the 50mm mean-sized particle, then...
dropped to 16% RSD for the 144mm mean-sized particles. It might be due to an artifact of the 2D image analysis. A single or even several 2-D projections of a non-spherical object, cannot fully capture its 3D shape (National Academics of Sciences, Engineering and Medicine, 2010). Due to gravity and settling behavior, length and width frequently faces to camera angle when capturing images from slope, while thickness is poorly presented. As Table 4.4 indicated, thickness varies considerably over the size ranges; however, it is highly possible for the thickness to be left behind, as the comparatively constant length/width ratio is palpably measured. Also, please note that images taken from the subparallel angle resulted in 19% larger equivalent spherical diameter, than the sub-perpendicular angle (which is the practical angle for drawpoint). It implies that bias is inherently introduced, depending on the projection of camera.

The limitation of 2D projection potentially leads to an error, unless distinctly defining the shape variability for the different size ranges. Also, it is interesting to note that the smaller size range tends to be more platy, as is seeing large width/height ratio for a smaller size. However, an explanation for this falls out of the scope of this research, and it might be due to different breaking mechanism for smaller rocks.

<table>
<thead>
<tr>
<th>Mean relevant aperture size, mm</th>
<th>Number of Sample</th>
<th>Length/Width</th>
<th>STDEV - Length/Width</th>
<th>Length/Height</th>
<th>STDEV - Length/Height</th>
<th>Width/Height</th>
<th>STDEV - Width/Height</th>
</tr>
</thead>
<tbody>
<tr>
<td>24.0</td>
<td>63.0</td>
<td>1.3</td>
<td>0.3</td>
<td>2.7</td>
<td>1.3</td>
<td>2.1</td>
<td>1.1</td>
</tr>
<tr>
<td>50.0</td>
<td>30.0</td>
<td>1.5</td>
<td>0.3</td>
<td>2.4</td>
<td>0.7</td>
<td>1.7</td>
<td>0.7</td>
</tr>
<tr>
<td>347.7</td>
<td>93.0</td>
<td>1.5</td>
<td>0.9</td>
<td>1.9</td>
<td>0.7</td>
<td>1.3</td>
<td>0.4</td>
</tr>
</tbody>
</table>
4.4 Concluding Remarks and Discussion

To draw a relationship between in situ and secondary fragmentation, output of each analysis should agree with each other. However, the simple transformation, using a spherical model, was considerably underestimating the real volume. The proposed WipFrag analysis-based volumetric transformation models is the practical solution for future users seeing appreciable correlation, and negligible error against an actual volume. There is an interconnection between shape and size. In the case of caved material, the smaller rocks tend to be more platy which might be due to breakage mechanism or simply due to geology and fabric. Also, the big discrepancy between actual mass versus 3 orthogonal measures-based prediction of mass, was observed from smaller particles, due to inconsistent shape factor. However, due to the inherent limitations of 2D image, and the most variable measures, the thickness is poorly reported which might lead to an inaccurate representation of true rocks.
Chapter 5: Characterization of Rock Mass Fragmentation for Cave Mining

5.1 Introduction

The DFN approach offers the opportunity to maximise the use of fracture data collected from the mapping of boreholes and rock exposures. Linear ($P_{10}$) and areal intensity parameters ($P_{21}$), acquired from core logs and mapping of excavations, are converted into volumetric intensity ($P_{32}$), which can be used as an indicator of rock mass (in situ) fragmentation (Rogers et al., 2014). The result is a 3D fracture model that is representative of the rock mass. This Chapter presents the method used to generate a DFN-based fragmentation model for an operating block cave mine located in Kamloops (British Columbia, Canada), using the here-proposed CFI plot from Chapter 2. The results are then compared to the secondary fragmentation curves generated using image processing techniques, which is discussed in Chapter 3.

5.2 New Afton Mine Overview

The New Afton Block Cave Mine is located in British Columbia, Canada. The copper gold mine’s daily throughput is estimated 17,500 tonnes and is being extracted from two caves. The adjacent West and East caves are located 615m below surface and their layout extends 800m in length and 150m in width.

The deposit is located within crystalline and polylithic fragmental volcanics and lesser monolithic intrusive breccias (informally named as BXF) and is transected by many faults which are commonly carbonate-healed (Davies, 2015). Figure 5.1 shows plan view of geological and structural features. Comparatively large number of faults occur in East Cave. Also, a less
competent unit, picrate bound the orebody to footwall side (South). The one of the principal intrusive, the monzonite in south central part of deposit represent the most competent rock type. The orebody’s rock mass rating (RMR\(_{1976}\)) within mine footprint ranges between 35-55. A lower mining rock mass rating (MRMR) corresponds to East Cave due to frequent fault occurrence. Orientation of main joint set is dipping 76° angle in 8° azimuth direction (Bergen et al., 2015).

Figure 5.1 Geological and major structures elements at the extraction level (Modified from Nadolski et al., 2017)

### 5.3 Data Collection Process and DFN analysis

#### 5.3.1 Data Collection

The importance of data collection, data uncertainty and variability in relation to DFN modelling has been discussed by Elmo et al. (2016). Those authors addressed fundamental questions relative to the level of data characterisation and steps required to generate a realistic DFN model. To what extent discontinuities can be sampled and which limitations are inherently introduced in the analysis by the sampling methods being adopted represents important aspects that should drive the collection of discontinuities data for DFN analysis (Elmo et al., 2014).
The data sets used in this Chapter for generating the DFN model include boreholes and mapping of rock exposures (drift mapping), Figure 5.2. Because the data was collected prior to considering the development of a DFN model, important parameters (e.g. fracture terminations) were not considered in the data collection process. Furthermore, some data was not well suited for building a detailed DFN model (Elmo et al., 2015). For example, only limited oriented boreholes data was available, and mapping of underground drifts was carried out using a scanline method, which makes difficult to obtain a relationship between \( P_{21} \) and \( P_{32} \). In other instances, zones of missing or broken core were reported using arbitrary fracture frequency values (e.g. 99 or 55 fractures per meter). Whereas broken core may indicate the presence of well defined (deterministic) faults or shear zone, it was found that using those numbers in the DFN generation process without a filtering method in place would have likely resulted in the overestimation of rock mass volumetric fracture intensity. As mentioned in the literature review, presence of veins may hold a significant impact on decreasing the strength of jointed rock blocks (primary fragmentation), and increasing the degree of secondary fragmentation. Therefore, the presence of veins might have implication for fines reporting at drawpoints. Even though veins data was flagged along rock cores, precise information (location and frequency) of veins was missing; therefore, it was decided to not include veins data in the DFN model.
For the reasons above, in the current study only 45 drill holes were used for analysis of fracture frequency. Unrealistic fracture frequency numbers were filtered out and replaced by a nominal value of 10 which can be considered a realistic threshold. This approach allowed for a better smoothing of the cumulative fracture intensity plots. The presence of potentially highly fractured zones was later re-considered in the block model in a deterministic manner by manually introducing fault zones.

5.3.2 DFN Analysis

The typical process involved in the generation of a DFN model requires the definition of i) fracture spatial model; ii) fracture intensity; iii) fracture orientation; iv) fracture size (length); and v) fracture terminations.
In the current analysis, the Enhance Baecher spatial model was preferred over other spatial models (e.g. fractal Levy-Lee or Nearest Neighbor), since there was not sufficient field data available to justify using either a Levy-Lee or Nearest Neighbor model.

Orientation data collected along the 11 drifts and the 4 available oriented boreholes, was highly dispersed (Figure 5.3). Field data that are characterized by a highly-dispersed scatter can be analysed using a bootstrap approach, whereby a statistical method based on multiple random samplings, with replacement from an original sample, is used to create a pseudo-replicate sample of fracture orientations (Rogers et al., 2010). Fracture terminations are not considered in the model, due to lack of data.

![Figure 5.3 Stereonet showing the scatter data for the 11 drifts and 4 oriented boreholes.](image)

The definition of fracture length in the context of DFN modelling requires differentiating between fracture trace length, determined from the mapping of rock exposures, and fracture radius, a DFN input. Once the distribution of fracture length is known, the distribution of fracture radius can be
assessed by analytical methods, such as those carried out by Zhang et al. (2000), or by simulated sampling. The latter approach was used by Liu (2016) to define the fracture radius distribution corresponding to the fracture length data mapped along the apex level drifts at New Afton (Figure 5.4). Results from Liu (2016) is adopted in the model.

Figure 5.4 New Afton Mine fracture length simulated sampling (modified from Liu, 2016)

Because local fracture intensity may vary considerably, cumulative fracture intensity (CFI) plots were used to identify zones of the rock mass where the average degree of fracturing remains constant over considerable lengths, e.g., 10s to 100s of metres (Elmo et al., 2014). Even if automated methods could be used to select changes in gradient (i.e., changes in fracture frequency), there would still be the need to use an objective approach to define when a change in gradient is significant as discussed in Chapter 3. A mathematical approach, based on a “Piecewise Linear Interpolation,” is applied to define gradient changes in CFI plots, Figure 5.5.
The main issue that had to be resolved during data processing was reconciling the fracture orientation, and the fracture intensity data collected along the apex-level drifts and 45 drill holes that formed the main data source for DFN analysis and modelling. Note that only 4 drill holes used in this analysis produced oriented drill core data. To account for directional bias, $P_{10}$ intensity properties could be converted to $P_{32}$ intensity properties, which are independent of scale and orientation, and can therefore be used to directly extrapolate intensities throughout the rock mass volume (Elmo et al., 2014). Non-directional $P_{32}$ fracture intensity values can be obtained using stereological relationships between fracture orientation and fracture intensity (Wang, 2006).

A method had to be devised to convert the $P_{10}$ intensity properties, measured for non-oriented cores, into orientation-independent $P_{32}$ intensity properties. The method involves grouping those boreholes that do not have fracture orientation data, according to their dip and azimuth. For each group, a simulated borehole (with average dip/azimuth) is then used to infer $C_{31}$ from $P_{10}$, using a
simulated sampling method. The analysis is carried out in three steps, using the code FracMan (Golder Associates, 2015; Dershowitz et al., 1998),

- A DFN model is generated, using selected parameters for fracture orientation and length within a 16m x 16m region;
- A simulated borehole is used to find the intersecting fractures, and calculate a simulated $P_{10}$; and
- The analysis is repeated 30 times, for four different assumed fracture $P_{32}$ intensities, and a linear relationship between simulated $P_{32}$ and $P_{10}$ values are established.

The process is visually described in Figure 5.6 (modified from Elmo et al., 2014). To account for the stochastic nature of the DFN model, 30 realizations were run for each defined $P_{32}$ value (1, 3, 5 and 7), to define the linear relationship between $P_{32}$ and $P_{10}$ (Figure 5.7). The procedure is repeated for each group of boreholes, depending on their dip and azimuth, as seen in Table 5.1.
Figure 5.6. Schematic of the process for determining C31 constant by simulation (modified from Elmo et al., 2014).

Figure 5.7. Example of determination of C31 constant by simulation.
To increase confidence of the conversion factor (C31) which is 1.635 for example, shown in Figure 5.7, every point, intersecting the population of thirty realizations of $P_{10}$ values are tested by student’s T-test to check if the point could represent the population. If the point is beyond the confidence interval, the conversion factor is changed manually until finding conversion factor accepts null hypothesis.

Table 5.1. Borehole classification based on dip and azimuth

<table>
<thead>
<tr>
<th>Borehole group ID</th>
<th>Range Dip angle (degree)</th>
<th>Dip direction (degree)</th>
<th>Calculated C31</th>
<th>Number of boreholes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.8</td>
<td>91.1</td>
<td>1.679</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>20.4</td>
<td>180.1</td>
<td>1.458</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>40.9</td>
<td>71.5</td>
<td>1.691</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>44-56</td>
<td>314-326</td>
<td>1.776</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>35-54</td>
<td>2-359</td>
<td>1.642</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>51-72</td>
<td>287-308</td>
<td>1.919</td>
<td>9</td>
</tr>
<tr>
<td>7</td>
<td>69-80</td>
<td>38-40</td>
<td>1.694</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>54-76</td>
<td>271-277</td>
<td>1.727</td>
<td>4</td>
</tr>
<tr>
<td>9</td>
<td>71-89</td>
<td>0-354</td>
<td>1.691</td>
<td>7</td>
</tr>
<tr>
<td>10</td>
<td>78.3</td>
<td>340.5</td>
<td>1.730</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>78-87</td>
<td>222-244</td>
<td>1.730</td>
<td>4</td>
</tr>
<tr>
<td>12</td>
<td>73-86</td>
<td>304-318</td>
<td>1.751</td>
<td>5</td>
</tr>
<tr>
<td>13</td>
<td>83.0</td>
<td>160.0</td>
<td>1.635</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>83-89</td>
<td>86-92</td>
<td>1.653</td>
<td>2</td>
</tr>
</tbody>
</table>

Note that only one simulated interval is used in the process shown in Figure 5.6. The calculated C_{31} coefficients are then assigned to the various multiple intervals defined along a given borehole, according to the CFI analysis (Figure 5.5 above), and the corresponding $P_{32}$ values are calculated.
5.3.3 P₃₂ Block Model

Once every interval along the boreholes is assigned a P₃₂ value, an interpolation process is used to generate a geostatistical P₃₂ block model, according to following steps:

- Bimodalism and outliers are determined from boreholes’ P₃₂ histogram;
- Composites are created to convert the boreholes’ division into a standardized length;
- A particular orientation of greatest continuity, is analyzed by comparing number of variogram maps with different orientations;
- P₃₂ value is distributed throughout the block model, using ordinary kriging; and major structures are included in the model in a deterministic manner.

From the borehole information (collar, position, trend and plunge) and depth at P₃₂ value, geostatistical in situ rock mass block model is possible to be calculated. There were a few outliers in P₃₂ attribute due to data processing, made during CFI plot. By removing outliers, 99 percent of data is considered in the analysis as shown in Figure 5.8.

![Figure 5.8 Pre-processing of P₃₂ value prior to spatial modelling](image)
The values were composited using a downhole run length of two metres. The P\textsubscript{32} block model with grid size of 10m height, 10m width and 10m length will be considered homogenous in a sense that fracture intensity is treated as an indicator of the rock mass while the model is not constrained by lithological or alteration domains.

Anisotropy of data or particular orientation of greatest continuity can be determined by mapping variograms in different orientations. Orientation of major axis, corresponds to dip 83° angle and azimuth 245° angle, resulted lowest variance for longest range. The orientation shows good agreement with orientation of main joint set 76°/8° (dip/dip direction). The interpolation parameters are listed in Table 5.2. The P\textsubscript{32} value is distributed throughout the block model using the conventional geostatistical method (ordinary kriging).

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Model type</th>
<th>Sill value</th>
<th>Major dip/az</th>
<th>Search Distance Major, [m]</th>
<th>Search Distance Semi-Major, [m]</th>
<th>Search Distance Minor, [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>P\textsubscript{32}</td>
<td>Spherical</td>
<td>0.55</td>
<td>83/245</td>
<td>211.17</td>
<td>137.12</td>
<td>77.66</td>
</tr>
</tbody>
</table>

New Afton geologists have mapped, logged and interpreted numerous faults. Detailed description of faults can be found from Bergen et al. (2015). Those major structures included in the block model by deterministic way. Twenty-three fault zones are triangulated by New Afton geology personnel and inserted in the model by assigning P\textsubscript{32} equal to 20, which takes 8% of total volume. Since the minimum cell size in the block model is 10m x 10m x 10 m, any fault with a thickness less than 10m would be overestimated in the block model. An alternative would be to either i) use a variable cell size (equivalent to grading a mesh in a Finite Element model); or ii) inserting the
faults as deterministic surfaces and add a “distance-to-fault” correction to the P32 intensity. The former option may be computationally difficult to implement, while the latter would require access to field data that were not available in this project. It is worth noting that the presence of fault can potentially resulted in transition zone (from host rock to fault zone) which also indicate highly fractured rock mass. An isometric view of the block model is shown in Figure 5.9.

![Figure 5.9 Geostatistical P32 block model](image)

### 5.3.4 Fragmentation Analysis

A cell mapping algorithm is used to provide an initial estimate of the rock’s natural fragmentation. The cell mapping algorithm works by initially identifying all the fracture intersections with the specified grid elements. This results in a collection of grid faces and connection information, which is then used to construct a Rock Block of contiguous grid cells (Elmo et al., 2010). Because it is not possible to run the cell mapping algorithm on the entire model (unless a relatively large grid
cell size is used), the alternative method consists of running small-scale, high-grid cell density
models of fragmentation, for any given underlying $P_{32}$ intensity value. The generation of 150 x
150 x 150 cells has satisfied level of research detail. For each $P_{32}$ value, six DFN realizations were
run to account for the intrinsic stochastic variability of the models.

The distribution of the $P_{32}$ intensity values from the block model (Figure 5.10), is then used to
define a weighted average distribution curve for in situ fragmentation, shown in Figure 5.11. The
in situ fragmentation is cut-off at 0.001, which is a constraint within the DFN model. According
to Rogers et al. (2014), rock mass fragmentation may rapidly change over small intervals of $P_{32}$.
The results suggest that coarser in situ fragmentation may be present in the West Cave, based on
the different (smaller) distribution of $P_{32}$ values, shown in Figure 5.10. The in situ fragmentation
curves for the East and West Caves are shown in Figure 11. Note that more frequent hang-up has
been reported in the West Cave compared to the East Cave. An analysis of fragmentation block
model versus observed hang-up event using PCBC software will expand on in Chapter 5. The finer
fragmentation of East Cave can be explained by the presence of transecting frequent faults in the
East Cave. Moreover, a now closed 255m deep open pit is located above the East Cave; blasting
and excavation of the pit walls might have contributed to the development of a halo of damaged
(i.e. more fractured) rock mass. This is not taken into consideration in the current DFN model, but
it should be considered for further studies of surface-to-cave interaction using DFN modelling.
Figure 5.10 Weight of $P_{32}$ on B1 and B2 blocks

Figure 5.11 In situ fragmentation based from the DFN analysis for varying $P_{32}$ intensities, and weighted averages for West and East Caves.
5.4 Comparison of Predicted and Measured Fragmentation Distribution

Within the framework of the cave to mill research group, secondary fragmentation measurements are collected from drawpoint muckpiles, and processed using two image-based measurement methods, Wipfrag and PortaMetrics. Drawpoints are selected, based on accessibility, variety of lithology, alteration, location and height of draws (HOD). In total, eighty-seven digital photos were taken periodically; the majority of which were processed using manual edge delineation, with WipFrag software (Figure 5.12). The manual delineation yielded good agreement with actual particle size distribution (PSD) comparing to PortaMetrics measurement (Liu et al., 2015). However, a key distinguishing feature of PortaMetrics is shorter manual delineation time and an automatic scaling function (Nadolski et al., 2017).

![Image processing of drawpoint muckpile using WipFrag solution, different colors refer to different rock size.](image)

Figure 5.12 Image processing of drawpoint muckpile using WipFrag solution, different colors refer to different rock size.

Figure 5.13 below illustrates the spatial location of drawpoint and the image based secondary fragmentation measurements along with corresponding HOD during the time of each
measurement. The bigger bubble indicates higher HOD. Majority of measurement is taken from the West Cave. Down to 100mm particles are recorded from the image-based method, because fines are considered to be effectively measured through sieving. More specifically, Nadolski et al., (2017) has collected and sieved two bulk samples of gyratory crusher product in scope of Cave-to-Mill research. Using technical parameter of the crusher, the gyratory crusher feed, which is secondary fragmented material at the drawpoint, if the effect of material handling is considered minimum, is estimated from back calculation (Nadolski et al., 2017). Note that the current analysis of rock fragmentation only used image-based measurements, which have limited capability for accurately measuring the fines.

![Spatial location of image based secondary fragmentation measurement, clustered based on similar HOD](image)

**Figure 5.13 Spatial location of image based secondary fragmentation measurement, clustered based on similar HOD**

Three drawpoints (F10N, C05S and E13S) are selected for further analysis considering their relatively different HOD in similar lithology (BXF). The three drawpoint is chosen to indicate
change of size distribution with respect to their different HOD and its corresponding fragmented material, including blaster material, primarily fragmented material and secondarily fragmented material.

Each secondary fragmentation measurement is logged on certain date; therefore, corresponding conventional ellipsoid flow theory based HOD can be calculated using PCBC software using input data, such as the recorded tonnes pulled up until to the date and delineated shape of each draw column of each drawpoint. According to date of the image based measurement, drawpoint F10N, C05S and E13S are estimated to have HOD 35m, 87m and 207m, respectively.

Within each draw column, and to the corresponding HOD, there are number of varying P\textsubscript{32} blocks. With an assumption that each block has a same weight on final distribution reporting at drawpoint, a weighted average block size distribution curve can be plotted as shown in Figure 5.14. Note that output of WipFrag based secondary fragmentation measurement is an equivalent sphere diameter of each particle. Both secondary fragmentation measurement which is in diametric estimation and in situ rock mass blocks which is volumetric estimation should agree with each other. Therefore, conversion factor, discussed in Chapter 4, is applied for WipFrag measurements.
Figure 5.14 Comparison between image based secondary fragmentation measurement and DFN-in situ rock mass

Note that the HOD is measured from the extraction level. The height between extraction level and the undercut is 20m on average. Also, height from undercut to apex level is 17m. Even though those three drawpoints cannot not represent the behavior of the whole cave, important observations can be made referring to Figure 5.14:

1. The in situ rock mass characterization in lower elevation (low HOD) tend to be less blocky whereas the rock mass in higher elevation corresponds to blockier nature of rocks, but obviously, geology and presence of major structure plays an important role;

2. The drawpoint C05S, a huge shift can be observed before and after the fragmentation takes place. Eighty-seven metres of HOD (from extraction level) can be dominated by primary
fragmentation. It can explain prohibitive effort of secondary blasting/breakage in lower HOD (the hang-up events will be discussed in Chapter 6);

3. The considerable shift of size distribution of the drawpoint F10 is a result of ring blast.

4. Gradient of in situ rock mass curve are agreeing well with gradient of secondary fragmentation curves, not considering finer portion of drawpoint C05S which might be due to riling and boundary effect (Figure 5.13.);

5. Secondary fragmentation plays dominant role as the HOD matures because if the effect of secondary fragmentation was minimum, the in situ rock mass distribution should have shift to left side in constant pace.

Two cubic metres block, which is considered oversized material for New Afton Mine, corresponds to 89%, 82.1% and 97% percent passing volume of in situ fragmentation for F10N, C05S, and E13S respectively.

5.5 Concluding Remarks and Discussion

This Chapter presented an alternative way of estimating fragmentation with the effective use of fracture data, collected from mapping and borehole. The collection of discontinuity data for DFN analysis requires considerable effort, but if it is not fulfilled, the practitioner should make necessary modifications, based on known limitations. In addition to the modification, mathematical approaches were suggested to find the constant interval of fracture intensity domain, rather than manually tracking interval boundaries.

After the conventional geostatistical approach is applied to spatially distribute P32 for the caving zone, the detected major structures come into play, by placing them in a deterministic way in the
block model. From the block model, the simulated in situ fragmentation size reveals that the West Cave will report coarser fragmentation, compared to the East Cave. This assumption is supported by operational history, where the frequent hang-up occurred in the West Cave.

In case of New Afton Block Cave Mine, the in situ rock mass in lower elevation is tend to be less blocky whereas higher elevation is blockier; however, geology domain plays an important role as seeing draw column lying above the C05S does not confirm the above mentioned conclusion. Also, the secondary fragmentation is significantly influenced by HOD as it is evident that the shift is inconsistent depending on HOD.
Chapter 6: Comparison Between In Situ Rock Mass and Operational Data

This Chapter is focused on the comparison between hang-up event (HUP) and the proposed in situ rock mass block model using PCBC software.

6.1 Introduction to PCBC Software

Gemcom PCBC™ is the planning and scheduling software of block cave mines. The software is not a geomechanical software such as Rebop (Itasca Consulting, 2000) and Cellular Automata (Alfaro, 2004; Sharrock et al., 2004), but, it performs set of empirical caving rules and assumptions which can be adjusted by the practitioner.

Prior to running production scheduler, a column of rock mass lying above drawpoint is constructed and stored as a “no mix” slice file from the user-defined draw cones shapes, (Diering et al., 2010). In this stage, various overlaps of draw cones are resolved to manage material double counting issue. The production scheduler tool runs based on given constraint and information such as development sequence of drawpoint, maximum draw rate, tonnage required on each scheduling period (Diering et al., 2010). For the operating mines, Caving Management System (CMS) and least squares and grade reconciliation (LSQ) tools are more relevant. The CMS tool aims to catch up long term production schedule when the historical tonnage differs from planned tonnage. When stored drawpoint assays data tend to deviate from the slice file data, LSQ tool offer alternative draw schedules by taking the change into account (Diering et al., 2010).

As mix of mechanism is subjected to caving area, the material may remain within the draw column (vertical mixing, erosion, compaction, inclined movement) or move to other draw column (riling
and horizontal mixing) or fall from outside (either through toppling or pit failure) (Figure 6.1). Diering (2007) has introduced Template Mixing approach which has incorporated above mentioned flow mechanism. Diering et al. (2010) stated main mechanisms for cave volume include vertical mixing, riling and erosion.

![Figure 6.1 Typical flow mechanisms in a block cave (Adopted from Diering, 2007)](image)

**6.2 Comparison Between Hang-up Event and P₃² Fragmentation Model**

From the time of caving is started, HUP is recorded via visual inspection on daily basis. There are large numbers of data comparing to image-based secondary fragmentation measurement. It is worth noting that visual inspection can be subjective because some drawpoint can have hang-up that cannot inspected visually; therefore, those drawpoints may still be classified as being ‘Active’ due to fines sieving through interlocking coarse boulders (personal communication, Stefan Nadolski, July 27, 2017). For example, it was observed that some drawpoint’s size distribution was a significantly different than adjacent drawpoint size distribution. It was observed while taking image based secondary fragmentation measurements.
Number of HUP on each month is divided by monthly tonnage to measure HUP frequency and to give a similarly weighted HUP intensity for each month. The hang-up event can relate to the corresponding HOD, as discussed in Chapter 5, Section 4.

The DFN based P₃₂ block model is appended to New Afton’s current PCBC project. Like other grades (such as Cu, Au, SG), each cell is assigned certain P₃₂ values. Using New Afton Mine’s PCBC parameter (such as shape and size of the draw column, and draw bell) as well as historic production schedule, PCBC historic production schedule runner, which is mostly used in LSQ and CMS tool, can report monthly P₃₂ values, and corresponding HOD for each drawpoint. It is process of back-calculating which blocks, high above the drawpoint, are reporting to drawpoint in each month with respect to estimated HOD. New Afton’s current template mixing model is utilized as a mixing model. Since conventional ellipsoid flow theory (REBOP, PCBC and cellular automata) is being questioned by recent flow marker experiment (Brunton et al., 2016), the HOD estimated from PCBC should be considered as an approximation.

The use of PCBC software offer flexibility for the comparison. Some drawpoints which are not extracted due to operational difficulty will have very low HOD while others are extracted heavily. Using the historic production schedule runner, P₃₂ values, reported monthly wise for each drawpoint, can take the effect.

**6.2.1 Drawpoint Based Analysis**

Two drawpoints (C05S and D13S) are chosen to illustrate drawpoint based analysis as shown in Figure 6.2. It might be interesting to see the how HUPs are being influenced by presence of fracture
in single draw column. Please note that HOD is measured from extraction level. Apparently, the drawpoint C05S has coarser blocks comparing to drawpoint D13S as seeing the low P_{32} value for drawpoint C05S. P_{32} values of drawpoint C05S increase until 40m and then consistently decreases. The hump shape is more conspicuous in drawpoint D13S. P_{32} value agree well with HUP events. The drawpoint C05S which has coarser blocks resulted in more hang-up than the drawpoint D13S did. Also, no HUPs is recorded between interval of HOD 120-150m where P_{32} values are lowest. According to experience in DOZ-ESZ Block Cave Mine, the HOD 120-150m is likely to see the effect of secondary fragmentation (personal communication, Allan Moss, August 4, 2017). However, a random hang-up events are still observed even after draw column matures (Bergen et al., 2015).

Figure 6.2 Comparison between HUP and P_{32} for drawpoint C05S and D13S
Since a sampling error and a local anomaly can heavily influence the drawpoint based analysis, a general conclusion cannot be reached from the analysis. The drawpoint based analysis can be effective after clustering drawpoints based on their location, lithology and stress environment.

### 6.2.2 Cave Scale Analysis

Next analysis is intended to identify general effect of in situ rock mass on secondary fragmentation with relationship to HOD. The analysis only covers West Cave because, from extraction level to HOD 141m (level 5211m – 5070m), there are limited numbers of data in East Cave (Figure 6.3). It is highly probable to distort the analysis and give a fallacious understanding about the East Cave.

![Figure 6.3 New Afton Mine cross section](image)

From the chosen slice of HOD across the West Cave, both P32 values and HUPs corresponding to each draw column are collected. Number of data for each slice varies depending on each HOD
because of varied maturity of draw column. Generally, large number of values can be derived from lower HOD. The highest number of data is collected from HOD 20-30m while lowest HOD correspond to HOD 180-190m, Table 6.1.

![Table 6.1 Quick statistics of data point]

<table>
<thead>
<tr>
<th></th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of data</td>
<td>370 (HOD 20-30m)</td>
<td>114 (HOD 180-190m)</td>
</tr>
<tr>
<td>Weight of P$_{32}$ equal between 9 and 10</td>
<td>4% (HOD 150-160m)</td>
<td>12% (HOD 50-60m)</td>
</tr>
<tr>
<td>Number of Hang-Up event</td>
<td>109 (HOD 20-30m)</td>
<td>18 (HOD 170-180m)</td>
</tr>
</tbody>
</table>

The data are clustered into 10 bins. All bins should have similar number of data; otherwise, each bin cannot be representative. MS Excel’s solver tool (2016) was run to distribute number of sample into each bin equally. Afterwards, each bin’s average P$_{32}$ values and correspond average HUP/thousand tonnes is found as shown in Table 6.2.

![Table 6.2 Example of distributing data points (West Cave HOD 10-20m)]

<table>
<thead>
<tr>
<th>Bins</th>
<th>Max P$_{32}$</th>
<th>Number of data</th>
<th>Average P$_{32}$</th>
<th>Averages HUP/kt</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9.2</td>
<td>16</td>
<td>7.0</td>
<td>0.8</td>
</tr>
<tr>
<td>2</td>
<td>10.2</td>
<td>15</td>
<td>9.8</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>11.0</td>
<td>14</td>
<td>10.6</td>
<td>0.4</td>
</tr>
<tr>
<td>4</td>
<td>12.0</td>
<td>14</td>
<td>11.3</td>
<td>0.5</td>
</tr>
<tr>
<td>5</td>
<td>12.8</td>
<td>16</td>
<td>12.4</td>
<td>0.5</td>
</tr>
<tr>
<td>6</td>
<td>13.5</td>
<td>15</td>
<td>13.1</td>
<td>0.4</td>
</tr>
<tr>
<td>7</td>
<td>14.0</td>
<td>17</td>
<td>13.8</td>
<td>0.3</td>
</tr>
<tr>
<td>8</td>
<td>14.3</td>
<td>17</td>
<td>14.2</td>
<td>0.2</td>
</tr>
<tr>
<td>9</td>
<td>16.0</td>
<td>17</td>
<td>15.1</td>
<td>0.1</td>
</tr>
<tr>
<td>10</td>
<td>17.4</td>
<td>18</td>
<td>16.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Stddeviation</td>
<td><strong>1.3</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

From the Table 6.2, scatter plot with 10 data points is drawn in Figure 6.4; each one of the points represents a bin with around 16 samples of draw column. The confidence intervals of those bins
are identical to each other. From the fitted exponential trendline, in situ rock mass natural fractures of HOD 10-20m is highly correlating to observed hang-up events. Furthermore, as the volumetric fracture intensity (P32) becomes lower (which implies coarser fragmentation), the HUP frequency is increasing. However, the higher HOD was showing different trend; it will be discussed more broadly later in this Chapter. Other plots with confidence interval and raw data are included in Appendix A.

![Figure 6.4 Example of cave scale analysis (West Cave across HOD 10-20m)]

From the all slices of HOD, consisted P32 ranges for all HOP is attempted to be retrieved to generalize an effect of HOD on P32 value. However, the consistent P32 range was fluctuating the number of data on each bin considerably. From the Table 6.3, averages of standard deviations of
each slice is considerably higher than altering $P_{32}$ for each slice. It can be explained by the heterogeneous nature of rock mass. For example, weight of $P_{32}$ between 9 and 10 is significant different for each slice of HOD as presented in Table 6.1. Therefore, different $P_{32}$ ranges is used for the next analysis.

### Table 6.3 Comparison between consistent $P_{32}$ ranges and altering $P_{32}$ ranges

<table>
<thead>
<tr>
<th>Slice HOD [m]</th>
<th>Deviation of # sample among bins (indicates if samples are distributed evenly)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Consistent $P_{32}$ ranges</td>
</tr>
<tr>
<td>10-20</td>
<td>9.14</td>
</tr>
<tr>
<td>20-30</td>
<td>18.72</td>
</tr>
<tr>
<td>30-40</td>
<td>16.67</td>
</tr>
<tr>
<td>40-50</td>
<td>13.49</td>
</tr>
<tr>
<td>50-60</td>
<td>12.49</td>
</tr>
<tr>
<td>60-70</td>
<td>8.61</td>
</tr>
<tr>
<td>70-80</td>
<td>9.89</td>
</tr>
<tr>
<td>80-90</td>
<td>9.61</td>
</tr>
<tr>
<td>90-100</td>
<td>9.26</td>
</tr>
<tr>
<td>100-110</td>
<td>16.05</td>
</tr>
<tr>
<td>110-120</td>
<td>12.72</td>
</tr>
<tr>
<td>120-130</td>
<td>14.72</td>
</tr>
<tr>
<td>130-140</td>
<td>12.41</td>
</tr>
<tr>
<td>140-150</td>
<td>13.84</td>
</tr>
<tr>
<td>150-160</td>
<td>13.92</td>
</tr>
<tr>
<td>160-170</td>
<td>10.68</td>
</tr>
<tr>
<td>170-180</td>
<td>10.47</td>
</tr>
<tr>
<td>180-190</td>
<td>9.48</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>12.34</strong></td>
</tr>
</tbody>
</table>

HOD slice intervals with 10 m, 20m and 30m are illustrated in the following figures. The block model grid size (10m x 10m x 10m) is compatible with height of those slices. Trendlines are drawn from the scattered raw data. From the scatter points of HOD 10-100m, the exponential trendlines
can be fitted while linear horizontal trendlines can be fitted for data of HOD 100-190m. It indicates that trendlines of lower HOD (10-100) show a high correlation between hang-up event and in situ rock mass blockiness, according to Figure 6.5. The hang-up events of higher HOD (above 100m) can hardly relate to natural fractures as seeing the horizontal linear trendlines. The HOD 60-70m was an exception in terms of following above mentioned trend.

**Figure 6.5 Cave scale analysis (10m interval slices - West Cave)**

Small interval length of HOD can be considered effective for capturing detail while large interval length of HOD is useful for concluding general trend. Figure 6.6 is a less busy graph where each slice of HOD had an interval of 20m. The hang-up frequency is being diminished steadily as HOD increases; but, starting from HOD 130m, hang-up has occurred almost randomly. Furthermore,
due to the averaging process, the detail of 10m slice is inherently lost for large slices as seeing the trendlines HOD 50-70m for both 10m slice figure, and 20m slice figure.

Figure 6.6 Cave scale analysis (20m interval slices - West Cave)
The rock mass, lying between extraction level to HOD 40m is heavily affected by ring blast because distance from the extraction level to the apex level is 37m in average. HUP frequency is correlating with presence of natural fracture intensity where the ground is damaged by ring blast. There might be a practical use of DFN for ring blast. Specifically, different blasting strategies can be used for different zones of rock mass. From blasted ground to upward, influence primary fragmentation and secondary fragmentation comes into play dominantly. The ratio of influence between primary and secondary fragmentation will alter depending on HOD. Presumably, HOD 40-70m can be fragmented under predominant influence of primary fragmentation mechanism and minor influence of secondary fragmentation mechanism as seeing the desirably correlating trendlines, Figure 6.7. Probably, starting from HOD 100 m, the fragmentation reporting at
drawpoint can be driven by mixture of primary and secondary fragmentation; however, it is assumed that secondary fragmentation mechanism might be a driving force as seeing the non-correlating linear trendlines.

6.3 Research Conclusion

DFN method is used to model cave scale in situ fragmentation. If the potential link between natural fracture and secondary fragmentation is identified, it could give a better insight for future lift’s fragmentation assessment. Also, the model proposed here can identify the worst period (low HOD) for hang-up frequency. Each chapter of the thesis chained together with purpose of building DFN based in situ rock mass and validating the model against operational data.

Chapter 2 lays out fragmentation assessment in realm of applied geomechanics and formulated a coherent research path.

In the Chapter 3, current data processing methodology for DFN model is questioned if there is a potential bias in data processing stage. It is concluded that CFI plots should be objective-driven. In case of modelling in situ rock mass for fragmentation assessment minimum interval length should be equal to or larger than, the grid resolution used for fragmentation analysis. Furthermore, human uncertainty can be introducing the so-called “close-up” effect (different users, using different scales may not see the same intervals).

Chapter 4 assessed effectiveness of image-based secondary fragmentation measurement. There was a good correlation between results from WipFrag software and actual volume; however, a big
deviation observed when converting two dimensional WipFrag result into actual volume. Since DFN models can be translated my volumetric size distribution, volumetric transformation model is proposed in the Chapter 4. Also, link between caved rock’s size and shape is discussed. It is concluded that a thickness of each rock which is the most variable measures for caved rocks is poorly reported which might lead to an inaccurate representation of true rocks.

DFN-based in situ fragmentation block model is developed in Chapter 5 where previous chapters comes into play as an input. The ordinary kriging estimate is applied to spatially distribute $P_{32}$ for the caving zone, the detected major structures introduced in the model deterministically. The West Cave is calculated to report coarser fragmentation, compared to the East Cave. This assumption is supported by operational data. The drawpoint based analysis attempted to explain an influence in situ rock mass on ring blast, primary fragmentation and secondary fragmentation

Chapter 6 addressed cave scale analysis using PCBC software. It is concluded that influence of natural fracture varies depending on HOD. There can be a significant implication of natural fracture network on effectiveness of ring blast. The effect of in situ rock mass on HUP diminishes gradually as the HOD increases. However, slice 60-70m is not following the above mentioned trend. Starting from HOD 100m, in situ fragmentation was not affecting secondary fragmentation reporting at drawpoint.
6.4 Recommendation for Future Studies

To the author’s opinion, DFN based fragmentation assessment requires further advancement in following areas:

1. Drawpoint based analysis can be studied comprehensively, since the cave can be subdivided into geotechnical and geological units;
2. P32 fragmentation block model can be validated against existing RMR, grade and geological block model;
3. Influence of vein can be incorporated into model since the similar studies identified role of vein on primary and secondary fragmentation;
4. Linkage between caved material size and shape can be studied against DFN based block shapes to identify possible links;
5. Fragmentation mechanism in both primary and secondary fragmentation need to be studied in further using description of DFN based natural fractures and other code to simulate fragmentation mechanism and mixing mechanism;
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Appendix A Cave Scale Analysis - 10m Interval Plots with Raw Data and Error Bars