An Investigation into the Time Dependent Deformation Behaviour of Open Pit Slopes at Gibraltar Mine, BC, Canada

by

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B.A.Sc., University of British Columbia, 2011

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**Approval**

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Abstract

Open pit slope instabilities experience a sequence of decelerating deformation events following changes in stress state due to blasts or mining. These deformation events are poorly understood. This thesis uses large databases of specific energy and slope radar monitoring data to characterise five slope instabilities. Eight different rheological and empirical curve-fitting models are applied to 24 deformation events to identify which model best approximates observed deformation. The best-performing model, the Fractional Maxwell model, is then applied to nearly 200 deformation events identified from the five slope instabilities. The resulting model parameters α, fractional viscosity, and A, magnitude of the response, are tracked and compared with deformation history, instability size and geometry, and blast size and location. Slope instabilities exhibit increasingly viscous behaviour with deformation as damage accumulates within the rock mass. The magnitude and likelihood of deformation events correlate with the proximity of the stress change to critical geological structures.

Keywords: Slope stability; rock mechanics; open pit mining; rheology; slope radar monitoring; specific energy
To my dearest Abby.
Acknowledgements

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Chapter 1.

Introduction

1.1. Background

Although the time-dependent deformation behaviour of open pit mine slopes is increasingly recognized as being important in characterizing the stability of rock masses, the pre-acceleration behaviour of rock slopes has to date received relatively little attention. Most of the research on predictive forecasting considers cases where slopes accelerated and subsequently collapsed. Once a slope has begun accelerating, there are several methods to predict a time-to-failure (Dick et al., 2015; Mufundirwa et al., 2010). However, when a slope has begun accelerating, it is difficult to stop, so although time-to-failure estimates are useful for evacuating personnel and equipment, they provide no opportunity to mitigate the slope instability.

A regressive movement, characterized by an abrupt increase in slope deformation in response to stress changes due to mine blasting or excavating, which subsequently slows, is much more common than collapse. Most instances of regressive movement do not result in acceleration or collapse, and instabilities that do eventually collapse typically begin as regressive-type movements (Zavodni, 2000). Excavating a bench at the toe of an instability, and observing the response is in effect a major, mine-scale experiment. The development of real-time and spatially comprehensive monitoring systems, such as radar, and remote sensing techniques including LiDAR, has provided the opportunity to quantify the effects and extent of deformation resulting from each such ‘experiment’ at greater scales and detail than previously possible. However, the resulting slope deformation data is often used only to guide safe-mining thresholds, or to calibrate back analyses once the slope instability is no longer mitigatable. The data is rarely used to understand slope deformation behaviour, characterize the instability, or predict future behaviour.

This gap in knowledge and practice has been previously identified and discussed. Using prism surveys and early radar data, Mercer (2006) attempted to analyse several pit slopes with differing rock masses and failure mechanisms and found that contrary to expectation, the pre-collapse deformation rate behaviour between different pit slopes was
very similar. Real-time monitoring however was still in its infancy, and some of the resulting input data was coarse; consequently, Mercer recommended further research including:

“… select case study mining operations which have comprehensive monitoring systems and relatively frequent failures and visit and work with the mining operations for a period of possibly one to two years studying and observing deformation behaviour first hand. In this time the researcher should participate in overseeing the collection and interpretation of very precise data as well as continually reviewing further development of monitoring systems as the pit geometry and circumstances change. Deformation measuring instruments should include radar, automated prism survey networks and inclinometers and possibly laser scanning.

Additionally, the researcher should record the location and time of all mining related events (such as blasting and excavation) as well as environmental events (seismic, rainfall, groundwater level, etc.). Further information collected should include regular (monthly) pit surveys. The development of a geological model using 3D visualization software is considered a necessity in order to study the interaction of structures on deformation and failures.”

The open pit slope deformation response to blasting and excavation can be predicted with some accuracy using advanced numerical modelling techniques. However, these techniques often require large quantities of time and data, a good understanding of the structural geology of the slope, and may involve several key assumptions. The main drawback of the analyses is that the time it takes to perform them can limit their usefulness on an operational or mine-planning time-scale. Such analyses are usually inappropriate for answering questions as to when the slope will slow to below response plan thresholds so that mining can continue or how the slope will respond to the next blast.

Rapid predictions of slope deformation from behaviour at recent excavation stages could be used to optimize mine planning. For example, mine operators could use equipment elsewhere in the pit if an unstable section of a pit slope is not expected to slow beneath operating thresholds until a specific later date. Predictions concerning the length of time a slope will continue to move after excavation of each bench could be used in decisions analysis to allow more accurate comparison of the cost of mining an unstable area with the cost of sterilizing the ore. Currently, such predictions are developed using varying levels of judgement and generally lack an empirical basis.

1.2. Objectives

The primary objective of this thesis is to investigate whether the deformation rate characteristics of five regressive unstable open pit slopes in the Granite Lake Pit, Gibraltar
Mine, BC can be used to better understand and characterize the slope instabilities and to predict their behaviour. This objective is achieved in two stages. First, several curve-fitting models were applied to the regressive deformation events of one slope instability case study to determine the best performing, most suitable model. This model was then applied to the slope deformation events of all the selected case studies to allow comparison of varied factors that potentially control deformation behaviour, including deformation history, rock mass strength, and mining location.

The secondary objectives of the research were to:

- Demonstrate how specific energy can be used to better understand and constrain faulting and the distribution of rock mass strength.
- Describe and characterize each of the slope instability case studies.
- Determine whether (and how accurately) curve-fitting models can be used to predict short-term deformation between mine blasts and slope excavation events.
- Determine whether, as suggested by Mercer (2006), deformation behavior is largely independent of the failure mechanism and mode.
- Characterize the change in pit slope rock mass quality, (i.e. pit slope damage) and change in behaviour as the pit slope deforms.

1.3. **Research approach**

The thesis has seven chapters. Chapter 2 reviews previous research on time-dependent deformation of open pit slopes and intact rock, slope failure prediction, specific energy, and slope monitoring methods.

Chapter 3 introduces the specific energy dataset, compares it to known faults, rock mass and intact strength, and proposes a method to utilize the dataset to better understand and map faults and rock mass strength. Specific energy is used throughout subsequent chapters.

Chapter 4 provides an overview of the Granite Lake Open Pit and describes the development, setting, and deformation history of each of the selected pit slope instability case studies.

Chapter 5 compares different empirical and rheological models to determine which is most suitable for modeling regressive open pit slope deformation. The Burgers and
Fractional Maxwell models were the best performing models with the Fractional Maxwell being the simplest to apply.

Chapter 6 applies the Fractional Maxwell rheological model to approximately two hundred regressive slope deformation events. The model constants are used to investigate possible correlations between slope displacement behaviour and pit slope displacement history, rock mass strength (damage), the slope instability size, groundwater, blast size, active mining bench, and distance between blasts and the centre of the instability.

Chapter 7 summarizes the research and recommends future work.

1.4. **Granite Lake Pit, Gibraltar Mine, BC**

Gibraltar Mine is a large copper-molybdenum development located approximately 50 km north of Williams Lake in central British Columbia (Figure 1). Gibraltar Mine was operated by Placer Development from 1973, when the mine opened, until 1996, when it was purchased by Westmin Resources. It closed in 1998 and was reopened in 2004 by Taseko Mines Limited which continues to operate the mine today (BGC Engineering Inc., 2015)
Gibraltar Mine includes four open pits: Gibraltar West Pit, Gibraltar East Pit, Granite Lake Pit, and Polyanna Pit. The subject of this study is Granite Lake Pit, which has been actively mined since the mine was reopened in 2004.

The Granite Lake Pit (Figure 2) has plan dimensions of approximately two kilometres by one kilometre, with typical slope heights of 300 m to 350 m and overall slope angles ranging from 33° to 44°. The ultimate pit is expected to have slope heights of up to 440 m. (BGC Engineering Inc., 2016)
Figure 2. UAV photogrammetry of the Granite Lake Pit, Gibraltar Mine, BC.
Chapter 2.

Literature Review

2.1. Time-dependent open pit slope deformation behaviour

Open pit slopes respond to excavation by deforming. Excavation alters the stress state of a rock mass, which strains as a result. Direct evidence of this phenomenon includes prism and radar monitoring records, and indirect evidence includes common features like tension cracks behind the slope crest and cracking along the slope itself (Zavodni, 2000).

One of the first discussions of the rheology of slope deformation was by Broadbent and Ko (1971). Following successful characterization of an accelerating slope failure, which exhibited exponential acceleration, a more precise monitoring system was set up to identify similar patterns as part of a three-million-dollar study by Kennecott Copper. The authors found “a disturbing number of exceptions in which the displacement function was apparently one of exponential decay, rather than acceleration” (Figure 3) and developed a rheological explanation using a version of the Kelvin-Voigt model (Eq. 1) to represent this type of behaviour.

Figure 3. Typical regressive movement (after Broadbent and Ko, 1971).

The proposed Kelvin-Voigt rheological model was:

\[ \mu = \frac{f}{K} \left(1 - e^{-\frac{Kt}{N}}\right) + \mu_o \]  

(1)

Where \( \mu \) is displacement, \( \mu_o \) initial displacement, \( f \) force difference, \( K \) elastic coefficient of the failure surface, \( N \) viscosity coefficient of the failure surface; and \( t \) time. The
force difference, \( f \), was thought to represent a combination of any imbalance between gravitational disturbing and resisting forces along the failure surface, seismic load from blasting, and a temporary load of elastic readjustments. In this model, the initial response is controlled by the triggering impulse and failure surface characteristics, and the decay in velocity is controlled entirely by the failure surface characteristics.

In this model, \( K, f \), and \( N \) cannot be independently determined; curve fitting can return only the ratios \( f/K \) (the amplitude component) and \( K/N \) (the velocity or time component). A simplified version of Eq. 1 (Zavodni and Broadbent, 1978) can be stated as:

\[
\mu = A(1 - e^{-\beta t}) + \mu_o
\]  

(2)

Broadbent and Ko (1971) observed that failures typically displace over multiple cycles and the failure characteristics \( A \) and \( B \) of one cycle generally depend on the previous cycle. However, as the slope geometries and the failure surfaces change with time and displacement, \( A \) and \( B \) also change with time and displacement.

Martin (1993) divided time dependent rock slope deformation behaviour (Figure 4) into three stages:

1. Initial response, where the open pit slope responds to mining by quickly deforming.

2. Strain hardening, where deformation rates decrease immediately after the initial response as shear strength within the rock mass is mobilized. Strain hardening is described as the “locking up of the rock mass through dilation”. Confusingly, this stage takes place during the ‘initial response’ stage.

3. Progressive failure, where the slope deformation begins to accelerate. This occurs as the shear strength of a rock mass decreases in response to continued deformation (strain softening). The shear strength of the rock mass, after declining, may reach a steady state, in which case the slope deformation will also occur at a steady rate. Or, the slope may accelerate and catastrophically fail.
Martin proposed that after each initial response and prior to failure, displacement rates decrease according to an exponential decay equation equivalent to the Kelvin-Voigt equation earlier proposed by Broadbent and Ko (1971):

$$R = Ae^{-bt}$$  \hspace{1cm} (3)

Where $R$ is displacement rate, $A$ and $b$ are constants, and $t$ is time. $A$ and $B$ depend on rock type, engineering geology, structural geology, strength properties, groundwater condition, slope geometry, and mining rate. Surprisingly, for individual case studies, Martin
uses the same decay constants for all events (deformation cycles) prior to the onset of failure.

The following guidelines for interpreting the slope displacement rates were given:

1. Slope movements of 0.1 mm/day indicate normal slope response behaviour.
2. Slope movements of 0.2 to 2 mm/day indicate strain hardening. Slope movement rates may continue decaying.
3. Slope movements of greater than 1 mm/day require increased monitoring to determine if the slope is undergoing strain hardening or progressive failure.
4. Movement rates greater than 10 mm to 100 mm/day indicate the slope may be undergoing progressive failure.

More recent work (Zavodni, 2000) has clarified Martin’s three overlapping stages as follows:

**Phase 1, initial response:**
Pit slopes respond to the changing stress state due to excavation and blasting by exhibiting rock mass dilation, relaxation, and elastic rebound. All pit slopes should experience this phase regardless of whether a failure surface or mechanism exists. Daily movement rates are highest immediately following excavation cycles and range from 0.1 to 4 mm/day. Annual movement rates are expected to be approximately 35 mm/yr. This movement may not significantly reduce rock mass strength.

**Phase 2, regressive failure (short-term decelerating displacement):**
The slope undergoes a series of significant (>1 cm/day) displacement cycles as mining progresses. These cycles can be characterized by an abrupt increase in displacement, followed by deceleration (Figure 5, curve A). The slope may or may not fully stop displacing between triggering events. Each cycle is thought to occur when the factor of safety in a slope temporarily drops below 1 (i.e. the driving force in the slope exceeds the resisting force); this causes the slope to move, evidenced by a spike in velocity which then decays as shear strength along the failure surface is mobilized. These conditions can be caused by excavation, mine blasting, earthquakes, or precipitation.

**Phase 3, progressive failure:**
The slope will experience accelerating displacement until collapse unless active mitigation is undertaken. Displacement often accelerates at a predictable, exponential rate.
Most significant progressive slope failures begin as regressive failure, and transition due to strain softening, changing pit geometry, and/or changing groundwater conditions.

Mercer (2006) continued work on time-dependent slope deformation behaviour by analyzing several detailed case studies. He determined that as suggested by Broadbent and Ko (1971), but contrary to Martin (1993), each mining event and displacement cycle is different, and regression parameters should be updated after each successive event. Mercer abandoned attempts to model behaviour using regression based on rheology, and instead suggested complex polynomial fits to displacement and velocity data (discussed in more detail in Chapter 5.3), and proposed an updated model of slope deformation behavior in response to mining involving five distinct stages, four of which are represented in

Figure 6:
1. **Pre-collapse, primary rock mass creep:**
   During Stage 1, the deformation rate peaks shortly after a blast and then rapidly decays until it reaches a steady state creep rate.

2. **Pre-collapse, secondary rock mass creep:**
   During Stage 2, the deformation rate is similar to stage 1, except that steady state creep is not achieved between events due to increased stresses within the slope. Deformation rates remain higher for longer, but still show decay after the initial acceleration.

3. **Post-onset-of-failure to collapse:**
   Stage 3 begins when the slope passes the onset-of-failure, and deformation rates no longer decay with time. Instead, slope deformation accelerates until collapse occurs.

4. **Post-collapse:**
   During Stage 4, the rock mass may initially continue accelerating, but soon stops deforming as the collapsed material impacts the pit bottom.

5. **Post-mining/recovery**
   Stage 5 indicates mining operations have ceased near the failure and the slope stabilizes.
Figure 6. Idealized time and event dependent deformation model for mined open pit slopes, leading to collapse. The red lines show horizontal displacement and the blue lines show vertical displacement. Modified after Mercer, 2006.
Rose (2011) compared the slope deformation estimated using a calibrated numerical model to the observed deformation in a pit slope (Figure 7). The resulting model roughly agrees with actual displacement but shows less pronounced increases in displacement following bench excavation and does not capture the regressive displacement of some of the later excavations. Figure 7 highlights an event (starting at bench excavation sequence 10) where actual displacement was slowing and may have stopped if mining had halted. Under the definitions established by Zavodni (2000), this would be classified as regressive, not progressive displacement. If the pit slope was continuously accelerating between bench blasts and excavations, it is implausible that the mine would be able to excavate a further six benches.

![Figure 7](image.png)

**Figure 7.** Actual vs. modelled displacement in response to bench excavation, highlighting a regressive displacement cycle in the ‘actual’ slope displacement. Modified after Rose (2011).

2.2. **Time-dependent deformation (creep) of intact rock and rock joints**

Time-dependent behaviour of intact rock, typically cylindrical samples of rock drill core, has been studied using uniaxial and triaxial testing (Aydan, 2016). Early triaxial tests on rock salt (Serata et al., 1968) showed that rock could exhibit two different behaviours, either viscoelastic or viscoplastic, depending on the stress conditions. When stresses were less than the yield strength of the rock salt, viscoelastic deformations occurred which showed good agreement with the Kelvin-Voigt rheological model, extended to three dimensions. If the stress exceeded the yield strength of the rock salt,
the rock experienced viscoplastic deformations. Later investigation suggested the Burgers viscoelastic model was superior the Kelvin-Voigt model for modeling the uniaxial compression of rock (Goodman, 1989). Recent testing (Ding et al., 2017) has shown that the Fractional Maxwell rheological model may be both superior to the Kelvin-Voigt and equivalent to the Burgers model (Figure 8), with fewer regression constants.

Uniaxial creep testing of Oya tuff (Ito & Akagi, 2001) showed that creep deformation behaviour could either progress to failure or reach a stable equilibrium at certain strain levels, depending on the applied stress ratio, calculated as the applied stress divided by strength (Figure 9).

Figure 8. A comparison of rheological fits to uniaxial compression testing data. Modified after Ding et al. (2017).
2.3. Slope failure prediction from monitoring data

The primary method for predicting slope collapse from monitoring data is the inverse velocity method, developed by Fukuzono (1985). When the inverse velocity of an accelerating slope is plotted against time, a trend-line through the data points can be projected to the time x-axis intercept, and represents the predicted time of failure (Rose, 2011; Figure 10).
Although widely used in practice, the inverse-velocity method has been shown to be sensitive to data averaging and can predict failure in a slope that only showed temporarily acceleration, resulting in false alarms (Venter et al., 2013). Dick et al. (2015) developed standard procedures for data averaging and monitoring point (or pixel) selection to help mitigate issues related to data averaging sensitivity, but interpreting temporary accelerations remains problematic.

Mercer (2006) suggested an alternate method of slope failure prediction, using an assumed displacement rate at collapse:

1. Clean the deformation data, removing outliers and incorrect data.
2. Normalize the data and then perform curve fitting, using an \( n \)-order polynomial of the logarithm displacements.
3. Determine the goodness of fit based on the difference between the measured data and the fitted curve.
4. Assess whether the fitted curve is ‘well-behaved’ beyond the limits of the measured data.
5. Differentiate the curve equation to determine the velocity and acceleration equations.
6. Use an assumed ‘displacement rate at collapse’ (1 m/day) to estimate a time of collapse.

**Figure 10. Inverse-velocity versus time for three different material behaviours. Modified after Rose (2011).**
7. Repeat the above steps as new data becomes available, restarting if a new mining event occurs.

This method shares the limitations of the inverse-velocity method i.e. it is only valid for accelerating slopes, it is only valid over periods where no mining events occur, and it does not address the question as to whether it is safe to resume mining in an area.

2.4. Specific energy

Specific energy in drilling terminology is defined as “the work done per unit volume excavated” (Teale, 1965) and calculated using the equation:

\[
SE = \frac{F}{A} + \left(\frac{2\pi}{A}\right)\left(\frac{NT}{u}\right)
\]  

(1)

Where \(F\) is thrust, \(A\) is area, \(N\) is rotation speed in revolutions per minute, \(T\) is torque, and \(u\) is penetration rate. Specific energy has units of force per area, typically given in kPa (SI) or psi (imperial).

Specific energy has been hypothesized to depend entirely on rock mass strength parameters and correlated with RMR’76 (Bieniawski, 1976), a measure of rock mass quality, as shown in Figure 11 (Exadaktylos et al., 2008).

![Figure 11. RMR vs. specific energy. Modified after Exadaktylos et al. (2008).](image)


2.5. **Slope stability radar monitoring**

Slope stability radar (SSR) is one of the most commonly used methods for monitoring open pit slopes, and as of 2011 over 150 GroundProbe and 80 Reutech units had been deployed. As of 2015, approximately half of the porphyry open pit mines in BC employed SSR (Nunoo et al., 2016).

Slope stability radar is popular because it provides some major benefits over traditional prism surveying:

- SSR can monitor a wide area from a distance and does not require the installation of prisms on a potentially dangerous slope.
- SSR provides almost real-time monitoring, with reading frequencies of just 10-20 minutes.
- This high reading frequency allows safe work under unstable slopes to continue for longer periods of time.

There are two primary types of slope stability radar: real aperture radar, commonly abbreviated as ‘RAR’, and interferometric synthetic aperture radar, abbreviated as ‘InSAR’. RAR systems scan the slope in a ‘pencil beam’ configuration and InSAR systems scan the slope in a vertical fan (Bellett et al., 2015). Both types of slope stability radar have improved in recent years in resolution, scan time, data acquisition and transfer, and features in recent years.

![Scan configurations for InSAR (left) and RAR (right). Modified after Bellett et al. (2015).](image)

Real aperture slope monitoring radar uses a traditional parabolic dish antenna to send radar waves toward a location along a slope and record the return. RAR systems calculate displacement as the phase shift between the transmitted signal and the return...
signal; displacements between subsequent scans greater than the wavelength (typically approximately 7.5 mm) are 'out of phase' and cannot be accurately measured. Under ideal conditions, RAR systems can measure displacement to sub-millimetre accuracy (GroundProbe, 2018), but under typical conditions accuracy is one to five millimetres. RAR systems also calculate ‘range’, the distance between the unit and the slope, from the signal’s travel time and the estimated speed of the wave. Because the speed of the wave depends on atmospheric conditions, error in the range parameter can range from several centimetres to several metres.

InSAR uses moving satellite-based or ground-based radar antennae to simulate a large ‘synthetic' aperture and produce high resolution displacement data. InSAR data processing techniques have advanced from differential InSAR, widely used in the 1990s (Massonnet & Feigl, 1998; Hanssen, 2001; Carnec & Delacourt, 2000), to permanent scatterer InSAR, developed in the early 2000s (Ferretti et al., 2001), to distributed scatterer InSAR, developed in 2011 (Ferretti et al., 2011). These advances, along with the availability of new and improved satellites, have increased the resolution, reliability, scanning frequency, and overall applicability of the satellite-based InSAR method to open pit monitoring and research. However, even the newest satellites have minimum revisit times of 4 days or more, so satellite InSAR cannot be used as a real-time monitoring method. (Colombo & Macdonald, 2015)

Ground-based InSAR (GB-InSAR) was developed in the 2000s to overcome the low scanning frequency and inflexible view geometry of satellite-based InSAR (Antonello et al., 2004).

GB-InSAR became commercially available in 2007, when IDS Corporation introduced the IBIS radar unit. By 2011 over 90 units had been commissioned (IDS Georadar, 2011). Since its development, the IBIS system has been used in numerous natural landslides (Barla et al., 2010; Dehls, et al., 2010; Lowry, et al., 2013) and open pit instability (Farina et al., 2011; Severin et al. 2011) studies. Several other GB-InSAR units have also been developed for research or commercial use (Monserrat et al., 2014).

One of the biggest advantages of GB-InSAR over satellite InSAR is higher scanning frequency. Scans can be repeated immediately after completion of the previous scan, which typically takes around five minutes (IDS Georadar, 2011). High
frequency scanning eases the identification and tracking of permanent scatterers and allows application of InSAR technology to real-time landslide monitoring and failure prediction.

Recent advances in monitoring radar technology include the ability to calculate 3D vectors where scans from multiple systems overlap. Radar measures line-of-sight displacement, but if multiple radar systems survey the same section of slope from differing view-angles, the vector angle of displacement can be estimated from the difference between the displacement magnitudes (IDS Georadar, 2018).
A New Method to Map Faults and Rock Mass Quality Distribution using Specific Energy

3.1. Introduction

Knowledge of the spatial distribution of rock strength is critical in understanding open pit slope deformation behaviour because rock strength can indicate the location of faults and weaker geotechnical units. Faults and weak units often cause and control pit slope deformation.

Gibraltar Mine have been collecting specific energy data, one measure of rock strength, from blast hole drilling since 2013. The Gibraltar specific energy data is calculated as the energy required to grind rock during rotary drilling (Teale, 1965), and is defined as:

\[ SE = \frac{F}{A} + \frac{2\pi}{A} \left( \frac{NT}{u} \right) \]  (4)

Where \( F \) is force or thrust, \( A \) bit area, \( T \) torque, \( N \) rotation speed, and \( u \) penetration rate.

3.2. Dataset and processing

The parameters used to calculate specific energy have been collected at Gibraltar Mine to help optimize blasts since October 29, 2013. These parameters are measured automatically during drilling; because of the high number of blast holes drilled during regular open pit mining, the dataset is large and covers the entire Granite Lake pit. It includes data from over 100,000 blast drill holes. The blast drill holes have an average depth of 16.8 m (55 ft) with specific energy measurements at 0.25 metre intervals. A typical drill hole has an average of over 65 specific energy measurements, and the total Granite Lake dataset includes over 6.5 million data points.
### 3.2.1. Data pre-processing

This very large dataset required pre-processing and cleaning to prevent errors and remove potentially misleading data from the visualized dataset. The following types of data were removed during initial data cleaning:

- Points with zero values for rotation speed, torque, penetration rate, interval drilling time, or weight on bit. These points were associated with infinite, very high, or very low specific energies and may not provide reasonable estimations of rock strength.

- Points with non-numeric values in any of the parameters required to calculate specific energy.

- Points in the specific energy dataset existing above the March 2013 lowest mined out surface; because specific energy data was first collected in October 2013, these data points may reflect waste rock drilling, not intact rock strength.

- Points in the dataset located outside of the Granite Lake Pit, which are either erroneous or irrelevant to the current study; this was performed by removing points that do not adhere to the following location criteria: $49000 < X < 57000$, $43000 < Y < 48000$, and $3000 < Z < 4500$.

- Duplicates, if a single point was included more than once in the dataset

### 3.2.2. The relationship between specific energy and depth

Specific energy appears to increase with drilling depth. For 50 randomly sampled drill holes (0.05% of the dataset), specific energy increases rapidly to a depth of approximately 5 m and increases more gradually below 5 m (Figure 13a). To account for local variation of rock quality, specific energy is normalized by the average specific energy of each drill hole; that is, specific energy at each point is divided by the drill hole average.

The depth vs. normalized specific energy relationship, averaged for the entire 100,000 drill hole dataset (Figure 13b), agrees with the 50-drill hole random sample: the top 5 metres are especially affected by depth, with specific energy of around 50% that of the overall average, and below this depth specific energy increases more gradually. The causes of the depth-specific energy relationship may include blast disturbance from mining of the previous bench, confining stress, the weight of the drill rods, and the possible presence of a layer of waste rock or slough on the bench being drilled.
To mitigate the influence of depth on the specific energy, the top 5 metres of each drill hole were removed from the dataset, and specific energy measurements below 5 metres divided by the average normalized specific energy at each depth. This decreases the recorded specific energy at deeper points in each hole, which are typically greater than average, and increases specific energy at shallower points in each hole, which are lower than average.

3.2.3. Bilateral filtering

Bilateral filtering is a noise-reducing filtering method primarily used in image processing. Similar to spatial averaging or Gaussian filtering, bilateral filtering replaces the value of each data point with an average of the surrounding points. In contrast to other methods, however, in bilateral filtering each value is replaced by an average weighted by the difference in magnitudes (and not just distance), resulting in better-preserved edges in the signal or image. This is important for the specific energy dataset, because one of the goals is to identify planar faults cutting through the Granite Lake Pit. Bilateral filtering was applied using the CloudCompare (2018) software package to reduce the noise in the dataset and enhance the visibility of planar concentrations of low specific energy cross-cutting the pit (Figure 14). Figure 14 also shows a DEM generated from UAV photogrammetry collected on April 2, 2017, the 10 Fault, and the 9 Fault.
Figure 14.  a) UAV photogrammetry of the Granite Lake Pit, highlighting 9 Fault and 10 Fault, b) the specific energy dataset, and c) the specific energy dataset after applying a bilateral filter.
3.3. **Comparison of specific energy data with known fault locations**

If specific energy is indeed related to rock mass strength, then faults, which are associated with damage zones where the strength is lower than the surrounding rock, should be visible as planar or sub-planar concentration of lower specific energy cross-cutting the data set. As previously presented (Figure 14), several such low specific energy concentrations are visible in the dataset.

To determine whether these planar features in the specific energy dataset are evidence of faulting, they can be compared with well-constrained faults from the 3D geological model. Two of the best-constrained faults exposed in the Granite Lake pit are 10 Fault and 9 Fault. Overlying these faults on a plan view of the specific energy data (Figure 15) shows good agreement between these faults and concentrations of low specific energy data, which are coloured as yellow to red points. Frequency distributions of specific energy at varied distances from these faults will be used to confirm this visual interpretation.

![Figure 15. Specific energy showing the 10 Fault and 9 Fault surfaces derived from the 3D geological model.](image)

**3.3.1. Specific energy and the 10 Fault**

10 Fault, the largest fault intersecting the Granite Lake Pit, is approximately 30 m wide. As at least five geotechnical drill holes intersect the 10 Fault, the specific energy
can be compared to rock mass quality. 10 Fault is visible as a band of low specific energy (Figure 16), in UAV photogrammetry (Figure 17a), and in LiDAR change detection as displacements occurring along the fault (Figure 17b). The LiDAR survey was completed from approximately 800 m using a Riegl VZ-4000 full waveform laser scanner. Change detection was performed using CloudCompare (2018) by computing the point-to-point distance between surveys scanned on June 14 and June 17, 2016. A comparison of the change detection analysis and low (less than 35 MPa) specific energy values is shown in Figure 17c.

![Figure 16. 3D 10 Fault model overlain on specific energy dataset.](image)

Specific energy distributions support the visual agreement between bands of lower specific energy and the 3D fault model. The Granite Lake Pit specific energy dataset has a median of 52 MPa and a mode of 49 MPa (Figure 18a). The rock mass within 46 m of 10 Fault has a reduced median (48 MPa) a similar primary mode (50 MPa), and a secondary mode between 20 and 30 MPa. The rock mass within 3 m of the 10 Fault shows a marked reduction in the median (36 MPa) and mode (27 MPa). Specific energy decreases approaching 10 Fault.

Five geotechnical holes intersect the pit near the 10 Fault, allowing the specific energy to be compared with rock mass parameters calculated for ‘runs’ or lengths of rock core returned from drilling. Rock Mass Rating (RMR76) decreases near the 10 Fault (Figure 18), similar to the specific energy data. The Granite Lake Pit has a median RMR76 of 59, a mode of 56, and a large secondary mode between 17 and 20. Within 46
m of 10 Fault, median RMR\textsubscript{75} values decrease to 52 (Figure 18b), and within 3 m of 10 Fault, to 27 (Figure 18c).

Figure 17. The 10 Fault, as seen in a) UAV photogrammetry, b) Riegl VZ 4000 LiDAR change detection showing displacement, and c) comparison with low specific energy (<35 MPa) data.
Figure 18. Specific energy and RMR\textsubscript{76} histograms for a) the Granite Lake Pit dataset, b) rock within 46 m of 10 Fault, and c) rock within 3 m of 10 Fault.

The RMR\textsubscript{76} and specific energy distributions shown in Figure 18 indicate that rock mass quality decreases close to 10 Fault. Sampling data at several distances from the 10 Fault indicates a consistent trend: the median specific energy and RMR\textsubscript{76} steadily decreases approaching the 10 Fault (Figure 19). The specific energy mode also decreases in discrete steps.
Median and mode specific energy, and median RMR₇⁶ for rock masses at selected distances from the 10 Fault.

3.3.2. Specific energy and the 9 Fault

The 9 Fault, another well-defined fault from the mine 3D fault model, also corresponds to a sub-planar zone of low specific energy (Figure 20). It appears to diverge from the low-specific energy zone, however, by over 15 m at some locations (Figure 20b).

Comparisons between 9 Fault and specific energy in a) plan and b) section view. The section view highlights the 15 m offset between the zone of low specific energy and the modelled fault.
The median and mode specific energy values within 46 m of 9 Fault are 44 MPa and 41 MPa (Figure 21b), lower than the pit-wide median and mode of 52 and 49 MPa. The median and mode within 3 m of 9 Fault are 40 MPa and 39 MPa. Although this decrease in specific energy data is consistent with the rock mass being weaker closer to the fault, the magnitude of the decrease is less than that observed for 10 Fault. This reduced decrease may be caused by a poorer correlation between the modelled 9 Fault and the 9 Fault expressed in the specific energy (Figure 20b shows that the modelled 9 Fault may be offset by 15 m). 9 Fault, with a thickness of approximately 10 m, is also thinner than the 10 Fault, which is approximately 30 m thick.

Figure 21. Specific energy histograms for a) the Granite Lake Pit dataset, b) rock within 46 m of 9 Fault, and c) rock within 3 m of 9 Fault.

Comparing median and mode specific energy at a wider range of distances from 9 Fault (Figure 22) shows a constant decrease in rock mass quality from within 50 m to within approximately 15 m of 9 Fault. Decreasing the distance cut-off further, from 15 m to 3 m, does not show a corresponding decrease in rock mass quality. This is indicative of the imperfect agreement with the 9 Fault as represented in the 3D geology model (Figure 20).
3.4. Comparison of specific energy with geotechnical unit rock mass parameters

Although specific energy should correlate to rock strength, no direct comparison of blast hole drilling specific energy and rock core UCS testing is possible, because core samples are not returned during blast hole drilling. A comparison of domain averages, however, is possible. The values for the UCS, GSI, and Specific Energy for each of the geotechnical units of the Granite Lake pit are presented in Table 1. Geotechnical unit boundaries (Figure 23) and UCS and GSI values for the geotechnical units are taken from the G5 Pit Design Report (BGC Engineering Inc., 2013). These geotechnical units are all comprised of tonalite; on average, WH contains the highest quality rock, and FLT, which includes faulted rock, contains the lowest quality rock. The other domains, EF, EH, and WF have similar UCS and GSI values to one another. Specific energy values presented are the mean for each domain, except for the FLT (faulted rock) specific energy, which is the mode specific energy of all data within 20 metres of the 10 Fault surface (i.e. a 40 m wide slice). Because of the inherent uncertainty in mapping of the fault, some data included in the 40 m wide slice represents non-faulted rock on either side of the 10 Fault, and the distribution shown in Figure 24 is bimodal. To more
accurately describe the fault character, the lower mode of the FLT specific energy distribution is used instead of the mean.

![Figure 23. Early geotechnical domains of the Granite Lake Pit (BGC Engineering Inc., 2013).](image)

**Table 1.** Comparison of geotechnical unit parameters (BGC Engineering Inc., 2013).

<table>
<thead>
<tr>
<th>Geotechnical Unit</th>
<th>Core Length Observed (m)</th>
<th>Blast Hole Drilling Length (km)</th>
<th>Number of SE Data Points</th>
<th>UCS (MPa)</th>
<th>GSI</th>
<th>SE (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLT</td>
<td>235</td>
<td>41</td>
<td>164251</td>
<td>15</td>
<td>35</td>
<td>27</td>
</tr>
<tr>
<td>EF</td>
<td>1233</td>
<td>470</td>
<td>1879865</td>
<td>87</td>
<td>60</td>
<td>51</td>
</tr>
<tr>
<td>EH</td>
<td>399</td>
<td>330</td>
<td>1320484</td>
<td>92</td>
<td>51</td>
<td>52</td>
</tr>
<tr>
<td>WF</td>
<td>399</td>
<td>32</td>
<td>129349</td>
<td>87</td>
<td>51</td>
<td>47</td>
</tr>
<tr>
<td>WH</td>
<td>2879</td>
<td>300</td>
<td>1198731</td>
<td>109</td>
<td>64</td>
<td>65</td>
</tr>
</tbody>
</table>
Figure 24. Data within 20 m of 10 Fault; the lower of the two modes is assumed to represent the fault specific energy distribution.

The results are scattered, and insufficient in number to define the relationship between specific energy, UCS, and GSI, but they do indicate a consistent trend, that specific energy increases with UCS and GSI (Figure 25).

Figure 25. Specific energy versus UCS and RMR$_{76}$.

Projecting the specific energy data onto photogrammetry data allows a smaller scale comparison of rock mass quality (and bench performance) and specific energy. An example showing photogrammetry results from northeast of the Granite Lake Pit (Figure 26) shows that a heavily faulted zone, evident in the benches as rubble, coincides with an average specific energy of approximately 30 MPa; a more minor fault cutting across the centre of the figure has an average specific energy of approximately 40 MPa, surrounded by a halo of increasing specific energy; and well-performing, good quality benches having an average specific energy of over 80 MPa.
Figure 26. The variation in specific energies of different quality rocks imaged using UAV photogrammetry a) without texture b) with texture, and c) with texture, coloured by specific energy within 10 m of each point.
3.5. Mapping faults from interpolated specific energy

The results of this research suggest specific energy correlates with strength, and low specific energies correlate with faults. However, directly mapping faults from millions of raw points, with coverage in three dimensions is challenging. The data are noisy and without cutting sections or further segmenting the data, only the outermost points of the three-dimensional data cloud are visible. One method of overcoming this limitation is to project the specific energy dataset onto the pit shell or (if available) photogrammetry, and then map faults from the results. This process involves:

- Assigning the average specific energy value within 15 m to each point on the destination point cloud or mesh.
- Applying a colour scale to the results on the destination point cloud or mesh.
- Selecting points along the centre of planar zones of low specific energy.
- Fitting a best-fit plane through the selected points.

In the example below, each point of a point cloud generated from UAV photogrammetry surveyed on April 2, 2017 (Figure 27a) is assigned the average specific energy value within a 15 m radius. Applying a colour scale from 0 to 60 MPa to the results of this assignment (Figure 27b) reveals several planar zones of lower specific energy intersecting the open pit slope. Points along one of these planar zones are selected, and a best fit plane generated to estimate the location and orientation (18°/333°) of the fault (13 Fault).

3.6. Summary

The analyses in this chapter were performed to determine whether the Granite Lake Pit specific energy dataset shows sufficient correlation with rock mass quality that it might be used to map and constrain faults and other weak zones within the open pit. First, the specific energy dataset near well-constrained faults was investigated and shown to decrease similarly to RMR$_{76}$. Then, representative specific energies were compared to the UCS and RMR$_{76}$ values per geotechnical unit. For both analyses, the precise relationship between specific energy and more commonly-used rock mass quality and rating parameters is not clear. The influence of jointing intensity and orientation on specific energy is also unclear. However, a general relationship is
apparent with specific energy increasing with rock mass quality, and this relationship is sufficient to be used to identify faults and zones of weak rock mass.

Figure 27. UAV photogrammetry from 2017-04-02 a) uncoloured, highlighting degraded benches associated with the 13 Fault and b) coloured by interpolated specific energy, showing picked points (white squares) and a best-fit plane.
Chapter 4.

The Granite Lake Open Pit

4.1. Gibraltar Mine Overview

4.1.1. Geology

The geology of Gibraltar Mine has been the subject of several studies (Ash et al., 1999; Ash & Riveros, 2001; Schiarizza, 2015). The Gibraltar ore deposit is hosted in a Late Triassic Granite Mountain batholith, which is interpreted to belong to the Quesnel terrane although it is surrounded by Cache Creek terrane rocks to the east, south, and west (Figure 28).

Figure 28. Location of the Granite Mountain batholith, the Quesnel terrane, and the Cache Creek terrane (Schiarizza, 2014).

Ash and Riveros (2001) describe the Cu-Mo deposit as: “… a Late Triassic, medium to very coarse-grained quartz diorite to tonalite intrusion that has been variably deformed, metamorphosed, and hydrothermally altered.” The Granite Lake Pit area is composed almost entirely of tonalite (Figure 29) that has undergone varying degrees of shearing and alteration; the most altered zones are foliated and schistose. Some small dykes are present.
Figure 29. Map showing regional geology (Schiarizza, 2014).
4.1.2. **Rock mass characteristics in the Granite Lake Pit**

The rock mass within the Granite Lake Pit is comprised primarily of generally strong (R4) tonalite with a variable texture, ranging from fine to coarse-grained, and a variable fabric, ranging from uniform to highly foliated. Rock quality is generally ‘Fair’ (41 < RMR < 60), with zones of ‘Poor’ (21 < RMR < 40) and ‘Good’ (61 < RMR < 80) rock. (BGC Engineering Inc., 2013)

Earlier pit design reports (BGC Engineering Inc., 2013) divide the rock mass of the Granite Lake Pit into five geotechnical domains (Figure 30; Table 2). Four geotechnical domains are defined by 9 Fault and 12 Fault. WF and EF represent rock mass to the west and east of 9 Fault in the 12 Fault footwall whereas WH and EH represent rock mass to the west and east of 9 Fault in the 12 Fault hanging wall. The FLT domain includes highly faulted rock, most of which is located near the 10 Fault. Domain averages are presented in Table 2. Later design reports (BGC Engineering Inc., 2015) added a sixth geotechnical domain, EE, which includes all rock east of EBF.

![Figure 30. Early geotechnical domains of the Granite Lake Pit (BGC Engineering Inc., 2013).](image_url)
Table 2. Early geotechnical unit properties of the Granite Lake Pit (BGC, 2013).

<table>
<thead>
<tr>
<th>Geotechnical Unit</th>
<th>Core Length/Thickness Observed (m)</th>
<th>Unit Weight(^1) (kN/m(^3))</th>
<th>UCS(^2) (MPa)</th>
<th>GSI(^3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLT</td>
<td>72</td>
<td>27</td>
<td>15</td>
<td>35</td>
</tr>
<tr>
<td>EF</td>
<td>376</td>
<td>27</td>
<td>87</td>
<td>60</td>
</tr>
<tr>
<td>EH</td>
<td>122</td>
<td>27</td>
<td>92</td>
<td>51</td>
</tr>
<tr>
<td>WF</td>
<td>122</td>
<td>27</td>
<td>87</td>
<td>51</td>
</tr>
<tr>
<td>WH</td>
<td>878</td>
<td>27</td>
<td>109</td>
<td>64</td>
</tr>
</tbody>
</table>

1. Unit weight is estimated as the average of values from laboratory testing.
2. UCS is estimated from point load testing; the point load conversion factor is based on a site-specific relationship between laboratory UCS testing and adjacent point load tests.
3. GSI is estimated from RMR\(_{76}\) averages calculated from drilling data.

More recently the geotechnical domain definition has been simplified to just two units (BGC Engineering Inc., 2016), with the justification that the variability of the rock mass parameters between the geotechnical units was lower than the variability within each unit. This justification appears to remain true even for the new, simpler geotechnical division of the Granite Lake Pit, which has just two primary units: tonalite bedrock (TON) and mineralized zones (MZN) (Figure 31). MZN has a slightly higher GSI of 75 and a slightly lower intact strength of 63 MPa, than TON, which has a GSI of 63 and an intact strength 89 MPa, for a similar overall shear strength envelope (Figure 32).

The shear strength envelopes (Figure 32) of the two rock units MZN and TON are similar, and their boundaries are not clearly defined. The rock strength in the Granite Lake Pit is highly variable, and in many locations, the rock mass has been locally weakened by faulting (Figure 33). In photogrammetry of the southwest wall, for example, the rock mass can be seen to vary from blocky, to blocky/disturbed/seamy, to disintegrated over two benches (Figure 34). Therefore, the MZN and TON units are not
considered in the analysis below; faults and local specific energy data are used to estimate rock strength rather than the similar unit averages.

Figure 31. Geotechnical units of the Granite Lake Pit (BGC Engineering Inc., 2016).

Figure 32. Rock mass shear strength envelopes for MZN and TON.
Figure 33. Photograph of the rock mass comprising the east pit slope, near the 13 Fault.
4.1.3. **Structural geology**

The structural history of the Gibraltar deposit is uncertain. The ore deposit is associated with zones of ductile deformation; this can be interpreted to indicate that batholith emplacement, mineralization, and deformation structures developed at the same time. However, recent work which included Ar-Ar and U-Pb dating, suggests that deformation may have occurred much later (Mostaghimi & Kennedy, 2015).

Mostaghimi and Kennedy (2015) describe the major structure groups as:
• Large, sub-horizontal to shallowly dipping, ductile, and compressive high-strain zones, associated with foliation, “S1”. Foliation is well developed close to the high-strain zones.

• North-south striking oblique-slip faults, containing foliated cataclasite

• Large faults dipping moderately to the west with thick gouge zones (e.g. Fault 10)

BGC (2015) performed a structural characterization of the Granite Lake Pit based on borehole televiewer, oriented core and photogrammetry data, and divided the Granite Lake Pit into six structural domains, corresponding to the previously described geotechnical domains (Figure 30). More recently, after collecting structural data from four new drill holes in the eastern Granite Lake Pit, BGC (2016) re-assessed the structural domains and determined that all structural data in the eastern, actively-mined area of the pit (where each of the case study instabilities are located) are best-represented by a single structural domain, because the same major discontinuity sets were observed across drilling data. A stereonet of this structural domain developed from terrestrial photogrammetry mapping is presented in Figure 35. BGC (2016) mapped fourteen discontinuity sets from this data. For this thesis, seven simplified discontinuity sets have been identified (Table 3). These sets include A1, a moderately southwest-dipping set associated with foliation, B1 and B2, which moderately dip to the northwest, B3, a shallow north-northwest-dipping set associated with major faults such as 13 Fault and 10 Fault, and E1, F1, and F2, which are sub-vertical sets dipping to the west, northwest, and north respectively. Relatively few east-dipping discontinuities have been mapped in from photogrammetry; this may be due to mapping bias: photogrammetric mapping has been performed predominantly on west-dipping pit slopes.

<table>
<thead>
<tr>
<th>Discontinuity set</th>
<th>Dip (°)</th>
<th>Dip direction (°)</th>
<th>Standard deviation (°)</th>
<th>Number of poles</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>50</td>
<td>209</td>
<td>18</td>
<td>127</td>
</tr>
<tr>
<td>B1</td>
<td>53</td>
<td>292</td>
<td>12</td>
<td>32</td>
</tr>
<tr>
<td>B2</td>
<td>58</td>
<td>321</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>B3</td>
<td>25</td>
<td>338</td>
<td>13</td>
<td>36</td>
</tr>
<tr>
<td>E1</td>
<td>77</td>
<td>265</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
<td>F1</td>
<td>81</td>
<td>346</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>F2</td>
<td>87</td>
<td>300</td>
<td>15</td>
<td>21</td>
</tr>
</tbody>
</table>
Residual friction angles for faults and fault gouge were estimated based on two sources: laboratory direct shear tests on faults with infill recovered from drill core (29 tests), and index testing on fault gouge samples (14 tests) using the approach of Stark and Hussain (2013), which uses clay fraction and liquid limit to estimate friction angle. The results of this testing indicate residual friction angles range from 21° to 27°.

Figure 35. Discontinuities mapped from photogrammetry and major faults from the 3D mine model within the active structural domain on a lower hemisphere, equal area projection stereonet. Modified after BGC, 2016.
4.2. **Slope instability case studies**

Five slope instabilities were selected for analysis in this thesis: G5NE Wedge, G5N, G5C, 10 Fault, and G5S (see Figures 36, 38, 39, and 40). These slope instabilities represent a variety of failure modes, slope geometries, and behaviour as discussed below, and together represent a long and varied history of mining and slope deformation response.

None of the slopes affected by these instabilities experienced a catastrophic failure or collapse, although the slopes exhibited large displacements (Table 4), high peak velocities, and temporary periods of acceleration.

![Figure 36. Location of pit slope instabilities in the Granite Lake Pit showing average velocities over high activity time periods.](image)

Strength distributions for each pit slope instability were estimated from the specific energy data within 7.5 m of each instability. The resulting distributions are presented as violin plots (Figure 37), combining box and whisker plots with an estimated frequency distribution of the data. The box and whisker plots show the second and third quartiles (the ‘interquartile range’) as a thick bar, the range of data as a thin bar (the
‘whisker’) and the median as a white dot. Around the box and whisker plots are the ‘violins’, kernel density estimates of the distribution of the data. Similar to normal distribution curves, the violins are tallest where data are most frequent, and shorter where data are less frequent.

Figure 37. Specific energy distributions for each pit slope instability.

Table 4. Pit slope instability summary.

<table>
<thead>
<tr>
<th>Pit slope instability</th>
<th>G5NE Wedge</th>
<th>G5N</th>
<th>G5C</th>
<th>10 Fault</th>
<th>G5S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total observed deformation (m)</td>
<td>10</td>
<td>20</td>
<td>18</td>
<td>58</td>
<td>76</td>
</tr>
<tr>
<td>Maximum size (m)</td>
<td>110 x 55</td>
<td>400 x 314</td>
<td>223 x 174</td>
<td>122 x 33</td>
<td>446 x 251</td>
</tr>
<tr>
<td>Height of instability (m)</td>
<td>122</td>
<td>229</td>
<td>229</td>
<td>122</td>
<td>274</td>
</tr>
<tr>
<td>Instability Mode</td>
<td>Wedge</td>
<td>Wedge</td>
<td>Toppling</td>
<td>Rock mass</td>
<td>Toppling</td>
</tr>
<tr>
<td>Number of Controlling Faults</td>
<td>2</td>
<td>3</td>
<td>Unknown</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Structural complexity</td>
<td>Simple</td>
<td>Complex</td>
<td>Complex</td>
<td>Rock mass</td>
<td>Complex</td>
</tr>
<tr>
<td>Median specific energy (MPa)</td>
<td>42</td>
<td>55</td>
<td>53</td>
<td>36</td>
<td>41</td>
</tr>
<tr>
<td>Overall slope angle (°)</td>
<td>32°</td>
<td>30°- 35°</td>
<td>33°</td>
<td>33°- 36°</td>
<td>33°- 36°</td>
</tr>
</tbody>
</table>
Figure 38. Location of pit slope instabilities in the Granite Lake Pit, overlain on UAV photogrammetry DEM.
Figure 39. Location of pit slope instabilities in the Granite Lake Pit, overlain on UAV photogrammetry DEM, coloured by radar displacement velocity averaged over the indicated time periods.
Figure 40. UAV photogrammetry DEM of the Granite Lake Pit overlain by specific energy data.
4.2.1. G5NE Wedge slope instability

Overview

The G5NE Wedge pit slope instability, which was active for a period from April to July 2015, is located in the northeast of the Granite Lake Pit (Figure 39). The overall slope angle near the G5NE Wedge slope instability is 32°/254°. This pit slope instability was initially believed to be composed of a series of wedges formed by an intersection of the 10 Fault, which has a local orientation of 30°/307° (dip/dip direction) and several persistent members of a fault set parallel to the Derek Fault (54°/219°). A third structure, GIB-2016-007 (38°/195°), had not yet been mapped when the slope instability was active. GIB-2016-007 is visible in aerial photogrammetry from April 2, 2017, and in the specific energy data, this structure defines the north side of the base of the slope instability, connecting the 10 Fault and Derek Fault just below the 1234 m bench (Figure 41, Figure 42). The slope instability is a wedge formed by the 10 Fault and GIB-2016-007, with a line of intersection plunging at 26°/261°. A cross-section perpendicular to the slope shows where the wedge daylights (Figure 41).

Based on the direct shear testing of faults with gouge infill, large structures in the Granite Lake pit are estimated to have residual friction angles of 22° to 27°. The line of intersection with a plunge of 26° (Figure 41) is shallower than the slope angle (and the slope angle along the line of intersection) and within the range of estimated residual friction angles, and daylights near the toe of the 1219 m bench.

Figure 41. Cross-section through the G5NE Wedge pit slope instability showing the open pit geometry on 2015-04-21, 2015-06-30, and 2015-11-01.
Photogrammetry from April 2, 2017 clearly shows the 10 Fault, Derek Fault, and GIB-2016-007 faults associated with bench degradation (Figure 42a), the pit slope instability geometry and radar velocity (Figure 42b), and specific energy (Figure 42c). A photograph of the G5NE Wedge instability, taken as mining was approaching the daylighting bench, shows its southern and northern limits (Figure 43).
Figure 42. Photogrammetry of the G5NE Wedge pit slope instability showing a) uncoloured DEM data, b) average slope velocity during June 2015, and c) specific energy (MPa).
**G5NE Wedge deformation history**

Movement of the G5NE Wedge slope instability appears to have begun in April 2015, with a small magnitude deformation event. The first major event with radar coverage (Figure 44) occurred in early May 2015, and in contrast to the other slope instability case studies, the movement geometry remains consistent over time. The slope instability does not significantly increase or decrease in area, except for extending slightly at the toe as mining progressed (Figure 45). The G5NE Wedge slope instability moved at very high velocities (the highest observed to-date in the Granite Lake open pit) following blasts in late May and June in the vicinity of where the wedge daylights. Each event is blast-triggered and immediately regressive following an instantaneous peak, except for the first major event in June 2015 (Figure 44d), which shows acceleration. As mining progressed past where the wedge daylights, the slope instability slowed (Figure 44f) and significant deformation ceased by July 2015.
Figure 44. Deformation and velocity of the G5NE Wedge during May – July 2015; a-f correspond with plots of meshed radar data in Figure 45.

Figure 45. Meshed radar data showing progression of the G5NE Wedge slope instability, May – July 2015.
4.2.2. **G5N pit slope instability**

*Overview*

The G5N slope instability (Figures 39 and 46), located in the easternmost area of the open pit, was active from August 2015 to May 2016. The pit slope orientation varies from 35°/317° along the south edge of the slope instability to 30°/269° along the north edge. Radar displacements of approximately 20 m were recorded over much of this pit slope instability. At its largest extent, the G5N slope instability was approximately 407 m wide and fifteen benches (229 m) high. The rock mass of the G5N slope instability (at the time of excavation) had a higher specific energy (61 MPa) than the overall average specific energy of the Granite Lake Pit (50 MPa) suggesting a higher overall rock mass quality, although a significantly weaker plane (Fault 13) undercuts the slope (Figure 47). The higher overall rock mass quality is evidenced by the clean, undamaged benches upslope of Fault 13, apparent even after the slope had experienced nearly 20 metres of deformation (Figure 47).

![Figure 46. Photograph of the G5N pit slope instability taken on January 27, 2016.](image)

The G5N Slope instability appears to be intersected and bounded by five faults (Figure 47). Two of these faults, GIB-2016-007 and Fault 13, appear to most strongly define the deformation (Figure 47b) and have very pronounced expression within the specific energy data (Figure 47c). Red Fault P1 (49°/277°) may constitute the back release. GIB-2016-007 (49°/195°) intersects the slope as a splay below the 1173 m bench oriented at 24°/195°. Fault 13 has an orientation of 18°/333°.
Figure 47. Photogrammetry of the G5N slope instability showing a) uncoloured data, b) average radar velocity during March 2016, and c) specific energy data.
The kinematic failure mode appears to be wedge sliding between Fault 13 and the primary GIB-2016-007 plane. A line of intersection between Fault 13 and the primary (non-splay) zone of GIB-2016-007 has an orientation (plunge/trend) of approximately 10°/276°, similar to the average prism displacement vector orientation in the north end of the moving block near GIB-2016-007. However, prism vectors farther from GIB-2016-007, in the faster-moving zone of the slope instability plunge more northerly, towards 306° (Figure 48). This may be related to the lack of confinement due to the pit slope geometry. As the pit slope orientation varies significantly, from 35°/317° along the south edge of the slope instability to 30°/269° along the north edge of the instability, farther from GIB-2016-007 the failure mechanism may effectively be planar sliding along Fault 13. Given the residual friction angle of 22° assigned to large faults, under dry conditions this instability should be stable whether controlled by the Fault 13/GIB-2016-007 wedge (plunging at 10°) or sliding along Fault 13 (dipping at 17°). Groundwater is likely an important factor affecting stability.

Interestingly, despite the large deformations (>20 m) and high velocities exhibited by the G5N pit slope instability, benches within the instability remained clean, and retained their structure. This may indicate that the G5N pit slope instability involves
limited internal deformation within the instability boundaries and may be moving predominantly as a block.

**G5N deformation history**

Major deformation of the G5N pit slope instability began in late August 2015, as mining occurred near the 1189 m bench in the northeast quadrant of the Granite Lake Pit. Movement occurred in an area roughly bounded by the 13 Fault and Red Fault (Figure 49a and Figure 50a). Only minor deformations were observed in the second half of September (Figure 49b and Figure 50b). Deformations increased in October 2015, during mining of the 1173 m bench, with the highest average deformation rates concentrating along the 13 Fault, which experienced approximately 5 cm/day in October 2015 (Figure 49c and Figure 50c). The slope instability increased in size in November 2015, though average deformation rates remained similar (Figure 49d and Figure 50d). In December 2015, the slope instability extended to the area between GiB-2016-007 and 13 Fault, and average deformation rates increased to a maximum of 8 cm/day, concentrating along 13 Fault as the 1158 m bench was mined (Figures 49e and 50e). Average deformation rates increased to between 10 cm/day and 15 cm/day as the 1128 m bench was mined in January 2016 (Figure 49f and Figure 50f).

In the first half of February 2016, mining activity temporarily ceased while horizontal drain holes were installed in the G5N slope instability. This can be seen in a decreased deformation and a lack of spikes in the velocity data in Figure 49g. However, the drain holes do not appear to have had a significant long-term effect, as deformation rates then increased to their maximum in March 2016 in spite of the increased drainage when the 1128 m bench was mined (Figures 49h and 50h). Average deformation rates decreased as the 1113 m bench was mined in April 2016 (Figures 49i and 50i). Although mining at the toe of the slope continued, mining through the 1097 m, 1082 m, and 1067 m benches from May to August 2016 (Figure 50j), the end of April 2016 appears to have marked the end of significant movements in the G5N pit slope instability.

The G5N pit slope instability appears to have been primarily controlled by Fault 13. Deformation was highest when material in the hanging wall of Fault 13 was removed. After mining progressed below Fault 13, movement slowed and then stopped.
Figure 49. Deformation history of the G5N pit slope instability, August 2015-June 2016; a – h correspond with plots of meshed radar data shown in Figure 50.
Figure 50. Average velocity of the G5N pit slope instability, Aug 2015 - June 2016.
4.2.3. **G5C slope instability**

**Overview**

The G5C pit slope instability is approximately 400 m wide by 370 m long and located in the southeastern wall of the Granite Lake Pit (Figures 39 and 51); movement was active from March to December 2016. The rock mass of the G5N pit slope instability (at the time of excavation) had a similar specific energy (48 MPa) to the overall average specific energy of the Granite Lake Pit (49 MPa) suggesting a similar rock mass quality. The open pit slopes of the G5C slope instability have inter-ramp angles of 36° to 37°, an overall slope angle of 33°, and are roughly 230 m high. A 30 m wide geotechnical berm (ramp) intersects the slope. Benches are 15 m high and generally 10 m to 15 m wide.

![Figure 51. Photograph of the G5C pit slope instability on March 29, 2016.](image)

The structural geology near the G5C Slope instability is less well understood than many parts of the Granite Lake Open Pit. Only two faults in the 3D fault model provided by Gibraltar intersect this slope instability, the EBF and Fault 12 (Figure 52). Neither of these faults are clearly expressed in the aerial photogrammetry model or closely match concentrations of low specific energy data (Figure 53).
The UAV and specific energy data (Figures 53a and 53b) show a number of scarps and faults (evident in bench degradation and roughly planar concentrations of low specific energy), and cross-cutting the slope instability, suggesting that there may be faults intersecting and controlling the slope instability that were not captured in the current 3D structural model. Although the failure mode has not been well-studied, the mode of instability may be toppling, evidenced by the reverse scarps highlighted in Figure 53a. The structure promoting toppling may be the steeply northwest to north-northwest dipping fault sets F1 and F2 (Figure 35). The G5C pit slope instability is clearly exacerbated by the presence of the faults.

One method of defining different zones within pit slope instabilities and determining whether strain is evenly distributed, or concentrated at certain locations or structures, is to take the spatial derivative (or spatial gradient) of the displacement velocity. Spatial gradients are commonly used to map and colour slopes (e.g. for slope aspect maps), but this technique has not previously been used for analysing slope velocity data in order to map or characterize landslides. Instead of showing the velocity of the slope, a 3D plot of velocity gradient shows the spatial changes in velocity with respect to position. If on one side of a one metre wide structure, the slope is moving 10...
cm/day, and on the other side 0 cm/day, the velocity gradient across the structure will be 10 cm/day per metre. On either side of the structure, (and in any zone with homogeneous slope displacement velocity) the spatial gradient is 0 cm/day per m. Taking the spatial derivative highlights a landslide’s outer boundaries and, if present, internal boundaries between blocks or zones moving at different velocities.

Figure 53. UAV photogrammetry (a) and specific energy (b) data, compared with faults from the 3D fault model, highlighting reverse scarps, cracks, and previously unidentified possible faults (orange).
Applying a spatial derivative to the October 2016 radar data for the G5C pit slope instability (Figure 54b), shows the outer boundary of the slope instability much more clearly than just showing the velocity itself (Figure 54a). It also clearly indicates that,
within the G5C pit slope instability, there exists a distinct faster-moving zone (the ‘primary zone’ in Figure 55).

![Spatial derivative (gradient) of velocity from October 2016, highlighting zones within the G5C pit slope instability.](image)

**Figure 55.** Spatial derivative (gradient) of velocity from October 2016, highlighting zones within the G5C pit slope instability.

**G5C movement history**

The G5C slope instability commenced in March 2016 with excavation of the 1128 m bench (Figures 56a and 57a). Movements were greatest in the 1158 m bench. Displacements increased in April 2016 and show a band of movement concentrated near Fault 12 (Figures 56b and 57b), although the highest rates occur to the south, away from Fault 12. In May 2016, the highest deformation rates recorded were on the 1128 m bench (Figures 56c and 57c). In the first half of June 2016, the slope instability was relatively inactive (Figures 56d and 57d) In the second half of June 2016, as mining reached the 1067 m bench, the slope instability increased in size and extended northward towards Fault 12, bounded by the EBF; during this period, movement appears to become controlled by unmapped structures, and lineations are visible in the velocity data (Figures 56e and 57e). In July 2016, the slope instability continued to progress northward past the EBF (Figures 56f and 57f). Average deformation rates were highest
in August 2016, with average movement rates of over 13 cm/day over a large area near the centre of the pit slope instability (Figures 56g and 57g). High movement rates continued through September 2016, with a spatial distribution similar to that of August 2016 (Figures 56h and 57h). Slope movements decreased in October 2016 (Figures 56i and 57i), and decreased further in November 2016 (Figures 56j and 57j), as active mining moved to other locations in the Granite Lake Pit.

Figure 56. Deformation history of the G5C slope instability, Feb 2016 – Jan 2017, a – b correspond with meshed radar data shown in Figure 57.
Figure 57. Average radar velocity of the G5C slope instability, March – November 2016.
4.2.4. 10 Fault Instability

**Overview**

Although the 10 Fault intersects large zones of the open pit slope on both the north and south walls of the Granite Lake pit, the 10 Fault slope instability refers to a single zone along the 10 Fault, in the south wall of the Granite Lake Pit east of the G5S slope instability (Figures 39 and 58). This instability exhibits ravelling and rockfall behaviour in a zone of weakened, sheared rock associated with the 10 Fault. Movements within the 10 Fault slope instability are likely influenced by the much larger G5S pit slope instability located just to the west (also visible in Figures 39 and 58). Movements within the 10 Fault slope instability however, which began in February 2016, appear to precede and be distinct from the G5S pit slope instability.

![Figure 58. The 10 Fault slope instability.](image)

- As of December 31\textsuperscript{st}, 2016, the open pit slopes near the 10 Fault slope instability have inter-ramp angles of 38°, an overall slope angle of 36°, an average dip direction of 46°, and are roughly 200 m high. Benches are 15 m high and generally 10 m to 15 m wide.
Figure 59. UAV photogrammetry of the 10 Fault slope instability showing a) uncoloured data, b) average radar velocity during April 2017, also showing prism vectors, and c) specific energy.
**10 Fault slope movement history**

The deformation along the 10 Fault pit slope instability, as measured in the radar monitoring data (Figure 60), is noisier than the other instabilities. This may be partly because sloughing instabilities are inherently more difficult to monitor with radar. The 10 Fault slope instability is a major source of sloughing and rock fall, causing radar, which measures the deformation between scans to record some error. Although the reflectors that make up a pixel are moving towards the radar station, some material may fall, revealing new reflectors farther from the radar station. Another source of error is view angle inaccuracy. Part of the later movement of the 10 Fault, and the rock mass upslope of the 10 Fault may be lateral, moving to the west in response to deformation of the G5S pit slope instability.

The 10 Fault slope instability was most active between May to November 2016, and April to June 2017 (Figure 60).

![Deformation history of the 10 Fault slope instability, March 2016 – July 2017.](image)

**Figure 60.** Deformation history of the 10 Fault slope instability, March 2016 – July 2017.
4.2.5. **G5S slope instability**

**Overview**

The G5S slope instability has experienced the greatest amount of deformation of any pit slope instability within the Granite Lake Pit, with observed radar deformations of over 70 m in some zones. Because radar only measures movement parallel to line-of-sight, this is likely an underestimation of the actual deformation experienced by the slope. The pit slope instability is approximately 446 m long by 250 m wide and is located in the south wall of the Granite Lake Pit (Figure 39). As of December 31st, 2016, the open pit slope of the G5S slope instability had inter-ramp angles of 37° to 39°, an overall slope angle of 36°, an average dip direction of 46°, and was roughly 213 m high. Benches within the G5S slope instability are degraded and difficult to identify.

At the time of excavation, the rock mass of the G5S slope instability had a lower specific energy (42 MPa) than the overall average specific energy of the Granite Lake Pit (49 MPa) suggesting a lower quality rock mass.

Deformation is controlled and affected by several faults which intersect and surround the unstable area. These include the 10 Fault, 8 Fault, 9 Fault, NF6 Fault, B2 Fault, Graben Fault, and NFG Fault (Figures 61 and 62).

The failure mode of the G5S slope instability is not fully understood but is thought to be a complex toppling failure, because at least three faults (Fault 8, Fault 9, and the Graben Fault) intersect the slope instability with toppling orientations (steeply dipping, sub-parallel to the pit slope; Figure 62). Furthermore, the instability morphology is typical of toppling, with major down-dropping near the crest and an uphill-facing scarp visible along the Graben Fault (Figure 62). There may also be sliding along the 10 Fault, which appears to define the base of the slope instability (Figure 63).
Figure 61. Fault intersections near the G5S slope instability.

Figure 62. Conceptual model of the G5S slope instability showing the instability geometry from UAV photogrammetry on November 2016, March 2017, and June 2017.
Figure 63. Photogrammetry of the 10 Fault and G5S slope instabilities showing a) uncoloured data, b) average velocity from April 2017, and c) specific energy.
**G5S slope movement history**

Figure 64 shows the radar velocity averaged over a small zone of the G5S slope instability near where the NFG fault and Fault 9 intersect (highlighted in a white outline in Figure 65). Different zones of what would eventually develop into the G5S pit slope instability exhibited movement as early as March 2016. Between March 20 and May 1, 2017, as the 1128 m bench was being mined near 10 Fault and NFG Fault, these faults experienced movements averaging greater than 5 cm/day (Figures 64a and 65a). During mining between July 13 and 20, 2016 (Figure 65b), two zones of deformation become more prominent in the radar data; in the east, a zone roughly bounded by the 10 Fault and Graben Fault, and in the west, a zone bounded by the NFG Fault and Fault 08. These zones continue to develop and increase in prominence through October 2016 (Figure 65c) and November 2016 (Figure 65d).

The G5S slope instability did not develop into a large and contiguous moving mass until December 2016, when the zones described above became connected through a rock mass weakened by the Faults 09, NF6, and B2 (Figure 65e). By February 2017 (Figure 65g), the slope instability is a contiguous moving mass exhibiting similar velocities across its extent. The slope instability experiences a large acceleration event over several days at the beginning of April 2017 (Figures 64j and 65j). The slope instability then slows until early May 2017, when it experiences another acceleration event, the greatest of any slope instability event considered in the current research (Figures 64k and 65k). In June 2017 the slope instability slows and recovers from this event. Gibraltar stopped mining at the toe of the G5S slope instability in June 2017.
Figure 64. Deformation history of the G5S slope instability, March 2016 – June 2017.
Figure 65. Radar velocity of the G5S slope instability, March 2016 – June 2017.
A comparison of the spatial derivative of velocity highlights the progression of the G5S slope instability over time. In October 2016 (Figure 66a), deformation is mainly limited to the initial instability zone, in the upper west zone of the slope instability, the 10 Fault, and the Graben fault. By April 2017 (Figure 66b), the 10 Fault and upper west zones of the slope instability have connected along B2 fault in the east. In the west, movement along NFG which initially partly truncated at Fault 08 extends further downslope to Fault 09. Although much of the instability is bounded by faults, which show high velocity gradients, the lower west zone (an apparent ‘key block’) exhibits a much more distributed strain. The lack of a structure connecting the NFG fault to 10 Fault at the toe of the instability may have prevented even greater deformation of the slope.
Figure 66. Spatial derivative of G5S velocity data from a) October 2016 and b) April 2017 interpolated on aerial photogrammetry.
Chapter 5.

The Application of Different Curve Fitting Models in Predicting the Short-term Behaviour of Open Pit Slopes

5.1. Introduction

Several curve fitting models have been proposed to predict the short-term deformation behaviour of slopes. Most models were developed before frequent, accurate deformation monitoring data were available, including exponential fits to deformation (Broadbent & Ko, 1971; Zavodni & Broadbent, 1978), and exponential fits to velocity (Martin, 1993). A later model, that fit polynomials to log deformation (Mercer, 2006) was developed using high frequency radar monitoring.

Most models were developed empirically, and some unreported redundancy exists between them. Martin’s (1993) exponential fit to velocity, for example, is simply the derivative of the exponential fit to displacement (Broadbent & Ko, 1971) proposed 20 years earlier. These mathematically equivalent models are sometimes presented as alternative solutions (Zavodni, 2000).

Martin’s (1993) exponential fit to velocity remains the most widely cited model, despite the noisy and infrequent data used to develop the model (Figure 67) and the author’s cautionary note that:

“Additional very precise monitoring data collected at much more frequent intervals would have been required to accurately define the time dependent relationship as they were affected by the mining process.”

Radar monitoring provides very precise and frequent data. As the quality of available monitoring data has greatly improved, these previously suggested curve-fitting models (Table 5) should be re-evaluated, with appropriate consideration of rheology, and compared with newer models to avoid redundancy and provide a physical basis for pit slope behaviour.
Figure 67. Data used to develop the exponential-decay velocity model (Modified after Martin, 1993).
Table 5. Models used to describe mining-triggered deformation events.

<table>
<thead>
<tr>
<th>Model</th>
<th>Formulae</th>
<th>Reference</th>
<th>Rheological Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quadratic</td>
<td>$\mu = At^2 + Bx + C$</td>
<td>(Voight &amp; Kennedy, 1979)</td>
<td>Empirical</td>
</tr>
<tr>
<td>Logarithmic</td>
<td>$\mu = A \log(t + 1) + B + Ct$</td>
<td>(Griggs, 1939)</td>
<td>Empirical</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Lomnitz, 1956)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Amadei &amp; Curran, 1980)</td>
<td></td>
</tr>
<tr>
<td>n-order polynomial to log displacement</td>
<td>$\mu = \exp(p_1 t^n + p_2 t^{n-1} + \ldots + p_n t + p_{n+1})$</td>
<td>(Mercer, 2006)</td>
<td>Empirical</td>
</tr>
<tr>
<td>Exponential fit to displacement</td>
<td>$\mu = A(1 - e^{-Bt}) + \mu_o$</td>
<td>(Broadbent &amp; Ko, 1971; Zavodni, 2000; Zavodni &amp; Broadbent, 1978)</td>
<td>Kelvin-Voigt</td>
</tr>
<tr>
<td>Exponential fit to velocity</td>
<td>$R = Ae^{-bt}$</td>
<td>(Martin, 1993)</td>
<td>Kelvin-Voigt</td>
</tr>
<tr>
<td>Exponential fit with steady-state creep</td>
<td>$\mu = - Ae^{-Bt} + Ct + D$</td>
<td>Current work</td>
<td>Burgers</td>
</tr>
<tr>
<td></td>
<td>$\mu = \frac{\sigma}{\eta_m} t + \frac{\sigma}{E_k} (1 - e^{-\frac{Ek}{\eta_k}})$</td>
<td>Current work</td>
<td></td>
</tr>
<tr>
<td>Fractional Maxwell</td>
<td>$\mu = \frac{\sigma}{E} + \frac{\sigma t^\alpha}{\eta^\alpha \Gamma(1 + \alpha)}$</td>
<td>Current work</td>
<td>Fractional Maxwell</td>
</tr>
</tbody>
</table>

5.2. Methodology

In this research curve fitting is applied to 24 selected deformation events observed in the Granite Lake open pit. ‘Mining events’ are defined as peaks (abrupt increases) in the velocity dataset. ‘Deformation events’ are defined as the data immediately following mining events. Deformation events extend to the lesser of a) three days after the peak and b) the next major trough in the velocity data (Figure 68).

Figure 68. Example mining and deformation events.
Deformation events selected for analysis in this chapter are from the G5N slope instability, which was deforming between August 2015 to May 2016. Results are assessed visually, theoretically, and using adjusted coefficient of determination (R²) values. To limit the effect of noise in the velocity data, curves are fit to deformation data to determine appropriate constants. The resulting fit is differentiated to determine a velocity model; R² for velocity is then calculated between the velocity model and the velocity data.

Because velocity is sensitive to reading frequency, resampling frequency, and calculation method, curve fitting to raw displacement data produces more repeatable results than fitting to velocity. However, velocity – not displacement – is the salient parameter; it is recognized as the best indicator of slope behaviour (Mercer, 2006; Zavodni & Broadbent, 1978), and as the most useful parameter for failure prediction. Best practice is to perform regression on displacement data, and then calculate the derivative to model velocity behaviour.

To identify models that over-fit to the data, and hence are generally less useful, curve fitting is applied to only the first half of data comprising each deformation event. The resulting model is compared against the full dataset comprising each deformation event to determine a ‘predictive R²’ value.

Adjusted R², which was developed to mitigate the inflation of R² values seen when explanatory parameters are added to a model, is used in this chapter to compare models with differing numbers of constants. Adjusted R², or $\bar{R}^2$, is calculated as:

$$
\bar{R}^2 = 1 - \left(1 - R^2\right) \frac{n-1}{n-p-1} \quad (5)
$$

Where $n$ is sample size, and $p$ is the number of explanatory parameters.

Full results of curve fitting to each of the 24 selected deformation events are presented in Appendix A. Four typical deformation events were selected from among the 24 events to compare the various curve fitting models; these comparisons are presented in Figures 69-72.
5.3. **Empirical models**

5.3.1. **The quadratic/linear model**

A quadratic fit to displacement is a simple model generally not used to describe pit slope behaviour, although it is one of the equations investigated in Voight & Kennedy (1979). It is presented here to provide a comparison against the ‘goodness of fit’ of more complex models. The quadratic fit to displacement has a linear derivative fit to velocity:

\[ \mu = At^2 + Bx + C \]  \hspace{1cm} (6)

\[ \frac{d\mu}{dt} = 2At + B; \]  \hspace{1cm} (7)

Where \( \mu \) is displacement, \( \frac{d\mu}{dt} \) is velocity, and A, B, and C are constants.

The quadratic fit closely agrees with measured displacements (Figure 69), although they slightly overestimate displacement in the first few hours, and underestimate displacement in the last few hours of each deformation event. Outside the range of data used to fit each curve, the quadratic fit displacement curve is unrealistic with a steep decrease in displacement. The quadratic displacement model has an average R\(^2\) value of 0.99. Note that this value is the average R\(^2\) of fits to all 24 deformation events; averages are tabulated in Table 6 (Chapter 5.5). Figure 69 shows model results for four representative events to illustrate and compare the different models.

Determining predictive fits, i.e. using only the first half of the data for each deformation event, shows the limitation of the quadratic/linear model (Figure 70). The predictive fits now clearly fail to conform to the data, with lower R\(^2\) values for displacement of 0.73.

The linear derivatives of the quadratic models (Figure 71) show poor agreement with velocity during the first day, although agreement improves in subsequent days. The quadratic/linear models have an average R\(^2\) value of 0.55, and an average predictive R\(^2\) value of -1.11.

There is no rheological basis for quadratic displacement behaviour, which is physically unrealistic. Recorded displacements do not reach a peak and then reverse direction, first slowly then at an increasing rate, moving rapidly away from the radar.
station. Despite this unrealistic behaviour, the quadratic fit visually and mathematically (i.e. in terms of the R²) conforms to fitted displacement data. Only after considering the derivative velocity fit and testing the fit by limiting the dataset to the first half of each deformation event does the poor fit become obvious.

5.3.2. The logarithmic model

The logarithmic model is a more commonly used empirical function to model rock creep (Amadei & Curran, 1980; Griggs, 1939; Lomnitz, 1956). This model was used as early as the 1930s, when Griggs (1939) recognized that the deformation response of a rock to a change in stress state can be a combination of two behaviour modes: “elastic flow”, deformation that decreases with time, and “pseudo-viscous flow”, deformation that remains constant over time. Deformation was defined as:

\[ \mu = A + B \log(t) + Ct \]  

Where \( A + B \log(t) \) represents elastic flow, \( Ct \) represents pseudo-viscous flow, and \( A, B, \) and \( C \) are constants. This equation was noted to reasonably approximate deformation, but does not perfectly model creep behaviour, because \( B \log(t) \) approaches negative infinity as \( t \) approaches zero.

Lomnitz (1956) made improvements to the ‘elastic flow’ component of the creep equation based on laboratory experiments on the creep of intact igneous rock. Time was replaced with \( t+1 \) and constants were changed to parameters linked to stress and material properties:

\[ \epsilon = \frac{\sigma}{\mu} [1 + q \ln(1 + at)] \]  

Where \( \mu \) is shear modulus, \( q \) is a creep constant, and \( a \) is a material constant. Subsequent testing on the shear behaviour along rock joints (Amadei & Curran, 1980) showed displacement to be a function of time:

\[ \mu = A \log(t + 1) + Bt + C \]  

\[ \frac{d\mu}{dt} = \frac{A}{t+1} + B \]
Where A, B, and C are constants.

The logarithmic model used in this research to fit the Granite Lake Pit slope displacement dataset was that of Amadei and Curran (1980), with C set to 0 because displacement is reset to zero at the start of each deformation event as part of the data pre-processing. The logarithmic models fit displacement data reasonably well (Figure 69), with an average $R^2$ of 0.95. Using only the first half of each dataset as input results in only minor reductions in goodness-of-fit (Figure 70), with an average predictive $R^2$ values for displacement of 0.83.

The logarithmic fit to the velocity (Figure 71), with an average $R^2$ of 0.69, is superior to the quadratic fit. The predictive fit to velocity (Figure 72) also shows comparatively good agreement, with and average predictive $R^2$ of 0.66. However, both the fit and predictive fit to velocity generally underestimates velocity for the first few data points of each event, and overestimates velocity after the first day.

5.3.3. The Mercer polynomial model

Mercer (2006) proposed the following method of generating n-order polynomial fits to log slope displacement following deformation events:

1. Clean the slope deformation data, removing outliers and spurious data
2. Normalize the data and then perform curve fitting, using an n-order polynomial of the logarithmic displacements
3. Determine the goodness of fit based on the difference between the measured data and the fitted curve
4. Assess whether the fitted curve is ‘well-behaved’ beyond the limits of the measured data
5. Differentiate the curve equation to determine the velocity and acceleration equations
6. Use an assumed ‘displacement rate at collapse’ (Mercer uses 1 m/day) to estimate a time of collapse
7. Repeat the above steps as new data becomes available, restarting if a new deformation event occurs.

Mercer’s (2006) suggested polynomial fits to log displacement data have the form:

\[ \mu = \exp(p_1 t^n + p_2 t^{n-1} + \cdots + p_n t + p_{n+1}); \]  \hspace{1cm} (12)

where \( n \) is polynomial order and \( p_n \) are constants. The derivative curves (i.e. velocity), have the form:

\[ \frac{d\mu}{dt} = ((n)p_1 t^{n-1} + (n-1)p_2 t^{n-2} + \cdots + p_{n-1} t + p_n) \exp(p_1 t^n + p_2 t^{n-1} + \cdots + p_n t + p_{n+1}); \] \hspace{1cm} (13)

Polynomial fits to displacement show excellent agreement with the data (Figure 69) with average \( R^2 \) values of 0.99, 1.00, and 1.00 for 2\(^{nd}\), 3\(^{rd}\), and 4\(^{th}\) order polynomials respectively (Table 6). Predictive fits (Figure 70) show progressively poorer agreement with higher order polynomials, with \( R^2 \) values of 0.92, 0.52, and -4.5E-8 for 2\(^{nd}\), 3\(^{rd}\), and 4\(^{th}\) order polynomials.

Derivative fits of these polynomials also show very close agreement with velocity (Figure 71), with \( R^2 \) values of 0.69, 0.86, and 0.86 for 2\(^{nd}\), 3\(^{rd}\), and 4\(^{th}\) order polynomials. In fact, 3\(^{rd}\) and 4\(^{th}\) order polynomials are close to the best ‘goodness of fit’ of any of the models tested in this research. However, these fits appear to increasingly ‘over-fit’ the data with higher orders and predict unrealistic behaviour beyond the data limits. Predictive velocity fits show extremely poor agreement (Figure 72), with average \( R^2 \) values of 0.56, -1.4, and -2.0E9.

5.3.4. Summary

The empirical models tested generally show good agreement with displacement data from deformation events (Figure 69), and the derivative models show reasonable agreement with velocity data (Figure 71). However, fits developed using only the first half of deformation event datasets as inputs reveal that these models perform poorly as predictive tools (Figures 70 and 72). The models often show unrealistic behaviour outside of the range of fitted data.
Figure 69. Empirical fits to displacement for four deformation events.

Figure 70. Predictive empirical fits to displacement.
Figure 71. Empirical fits to velocity for four deformation events.

Figure 72. Predictive empirical fits to velocity.
5.4. Rheological models

5.4.1. Overview

Numerous rheological models have been proposed to model rock creep. Common rheological models (Figure 73) include Hooke’s Law, Newton’s Law, the Maxwell Model, Kelvin-Voigt Model, and Burgers Model (Aydan, 2016). Much of the work on time dependent deformation of open pit slopes has focused on empirical observations with little emphasis on the theoretical and rheological basis for the behaviour of a slope. However, some components of this work are consistent with rheological theory; Martin’s (1993) exponential-decay model, for example, is functionally equivalent to the Kelvin-Voigt rheological model. A discussion of simple rheological models is necessary to avoid future redundancy and provide required background.

![Schematic diagrams of rheological models.](image)

**Figure 73.** Schematic diagrams of rheological models.

a) Hooke’s Law

The Hooke elastic model describes a perfectly elastic material response, stating that the strain is proportional to applied stress according to the elastic or Young’s modulus of that material where:

\[ \varepsilon = \frac{\sigma}{E} \]  \hspace{1cm} (14)

Where \( \varepsilon \) is strain, \( \sigma \) is stress, and \( E \) is elastic modulus. Hooke’s law describes an idealized instantaneous and recoverable response: a change in stress results in an
immediate strain. In rheological schematics this is symbolized by a ‘Hooke spring’ (Figure 73a).

b. Newton’s Model

The Newton model is the simplest model proposed to describe viscous behaviour and states that strain rate is proportional to stress according to the viscosity of a material. When a constant stress is applied, the material will undergo strain at a constant rate. Strain and strain rate are calculated as:

\[ \varepsilon = \frac{\sigma}{\eta} t \quad (15) \]

\[ \frac{d\varepsilon}{dt} = \frac{\sigma}{\eta} \quad (16) \]

Where \( \varepsilon \) is strain, \( \sigma \) is stress, \( \eta \) is viscosity or viscosity modulus, and \( t \) is time. In rheological schematics, this is symbolized by a ‘Newton dashpot’ (Figure 73b).

c. Maxwell Model

The Maxwell model (Figure 73c) describes a material that exhibits both elastic (Hooke’s Law) and viscous (Newton model) behaviour components, combined in series. Strain and strain rate are therefore calculated as:

\[ \varepsilon = \frac{\sigma}{E} + \frac{\sigma}{\eta} t \quad (17) \]

\[ \frac{d\varepsilon}{dt} = \frac{\sigma}{\eta} \quad (18) \]

Where \( \varepsilon \) is strain, \( \sigma \) is stress, \( E \) is elastic modulus, \( \eta \) is viscosity or viscosity modulus, and \( t \) is time. In rheological schematics, this is symbolized by a Newton dashpot and a Hooke spring acting in series (Figure 73c).

d. Kelvin-Voigt Model

The Kelvin-Voigt model (Figure 73d) describes a material that exhibits elastic and viscous behaviour acting in parallel. Strain and strain rate are calculated as:

\[ \varepsilon = \frac{\sigma_o}{E} \left(1 - e^{-\frac{t}{\eta}} \right), \quad (19) \]
Where $\varepsilon$ is strain, $\sigma$ is stress, $E$ is elastic modulus, $\eta$ is viscosity or viscosity modulus, and $t$ is time. In rheological schematics, this is symbolized by a Newton dashpot and a Hooke spring acting in parallel (Figure 73d).

e. Burgers Model

The Burgers model describes a material that exhibits Maxwell and Kelvin-Voigt behaviours combined in series. Strain and strain rate are calculated as:

\[
\varepsilon = \frac{\sigma_0}{E_m} t + \frac{\sigma_0}{\eta_m} (1 - e^{-\frac{t}{\eta_k}}) \quad (21)
\]

\[
\frac{d\varepsilon}{dt} = \frac{\sigma_0}{\eta_m} + \frac{\sigma_0}{\eta_k} e^{-\frac{t}{\eta_k}} \quad (22)
\]

Where $\varepsilon$ is strain, $\sigma$ is stress, $E_m$ is Maxwell elasticity, $E_k$ is Kelvin-Voigt elasticity, $\eta_m$ is Maxwell viscosity, $\eta_k$ is Kelvin-Voigt viscosity, and $t$ is time. In rheological schematics, this is symbolized by a Maxwell and Kelvin-Voigt elements acting in series (Figure 73e). The strain behaviour of the Burgers model is compared with the other simple rheological models in Figure 74.

![Figure 74. Strain behaviour of simple rheological models.](image)

f. Fractional Maxwell Model
The Fractional Maxwell model has recently been used to model deformation of sandstone (Ding et al., 2017). This model replaces the Newton dashpot in the Maxwell model with an Abel dashpot, defined by the second term in Eq. 22. Strain and strain rate are calculated as:

\[ \varepsilon = \frac{\sigma}{E} + \frac{\sigma}{\eta^\alpha \Gamma(1+\alpha)} \]  
\[ \frac{d\varepsilon}{dt} = \frac{\alpha \sigma}{\eta^\alpha \Gamma(1+\alpha)} t^{\alpha-1} \]  

Where \( \varepsilon \) is strain, \( \sigma \) is stress, \( E \) is elasticity, \( \eta \) is viscosity, \( \alpha \) represents fractional differentiation, and \( t \) is time. \( \Gamma \) is the mathematical gamma function. In rheological schematics, the Fractional Maxwell model is symbolized by an Abel dashpot and a Hooke spring acting in series (Figure 73f).

When \( \alpha = 0 \), the Fractional Maxwell model is equivalent to a Hooke spring where deformation is instantaneous and does not have a time-dependent component:

\[ \frac{d\varepsilon}{dt} = \frac{\alpha \sigma}{\eta^0 t} = 0 \]  

When \( \alpha = 1 \), the Fractional Maxwell model is equivalent to an idealized Newtonian fluid, with a constant rate of strain:

\[ \frac{d\varepsilon}{dt} = \frac{\alpha \sigma}{\eta^1} = \frac{\sigma}{\eta} = constant \]  

Between these two boundaries, when \( 0 < \alpha < 1 \), the model is a fractional combination of both (Figure 75).
Figure 75. Fractional Maxwell Model with varying fractional constant $\alpha$.

5.4.2. Application of the Kelvin-Voigt model to slope deformation

Curve fitting to slope deformation response to deformation events has generally followed the work of Broadbent and Ko (1971) who suggested the following rheological model:

$$\mu = \frac{f}{K} \left( 1 - e^{-\frac{Kt}{N}} \right) + \mu_o$$  \hspace{1cm} (27)

Where $\mu$ is displacement, $\mu_o$ initial displacement, $f$ force difference, $K$ elastic coefficient, $N$ viscosity coefficient; and $t$ time. Zavodni and Broadbent (1978) describe a simplified version of this equation:

$$\mu = A \left( 1 - e^{-Bt} \right) + \mu_o$$  \hspace{1cm} (28)

Where $A$ is the amplitude coefficient, and $B$ is the time coefficient. In this model, velocity, the derivative of deformation with respect to time, is therefore:
\[ \frac{du}{dt} = \frac{f}{N} e^{-\frac{Kt}{N}}, \quad (29) \]

or more simply, \( \frac{du}{dt} = AB e^{-Bt} \quad (30) \)

Assuming \( f, K, \) and \( N \) (or \( A \) and \( B \), in the simplified equation) remain constant during the deformation response to individual deformation events. This is functionally equivalent to the exponential relationship used by Martin (1993) to describe displacement rate decay, although with a different notation:

\[ R = Ae^{-bt} \quad (31) \]

The above equations (21 – 25) are all forms of the Kelvin-Voigt rheological model. The principal difference between Martin’s approach and earlier work is that Martin fits directly to velocity data, whereas Broadbent, Ko, and Zavodni fit to displacement data.

Applying the Kelvin-Voigt model to event-induced deformation of the Gibraltar mine results in fits which closely resemble actual slope behaviour (Figure 76), although the fits slightly overestimate displacement during the first two to four measurements, and slightly underestimate the displacement during the last few measurements. Goodness-of-fit as measured using \( R^2 \) is very high, at 0.99. The fit’s behaviour past the range of fitted data appears reasonable. Determining fits using only the first half of each deformation event’s data (Figure 77) causes the models to underestimate displacement in the second half of the data monitoring, with a predictive \( R^2 \) of 0.90.

The derivative fits poorly match the first few data points, where measured velocities far exceed the modelled rates (Figure 78). After the first few data points, the Kelvin-Voigt model fits velocity well. Overall, the fit captures the variation seen in the velocity data, with an \( R^2 \) of 0.75, although only marginally better than a linear fit, which has an \( R^2 \) of 0.598. With regards to the predictive fits (Figure 79), the models underestimate velocity in the second half of each deformation event but have an improved fit to the first half of each deformation event, with the average \( R^2 \) decreasing only slightly to 0.71.

The Kelvin-Voigt is the most commonly-used rheological model for pit slope deformation. The Kelvin-Voigt behaviour is intuitive and matches expected behaviour;
after a blast, velocity spikes and then decreases as shear strength is mobilized, eventually reaching steady-state.

5.4.3. **Application of the Burgers model to slope deformation**

The Burgers model is equivalent to the Kelvin-Voigt model except that it assumes that deformation decays to a constant rate, rather than zero, at $t = \infty$. This model was selected for analysis because following several deformation events, deformation remained relatively constant or decayed more slowly between events than can be approximated using the Kelvin-Voigt model (see Chapter 3; the G5N pit slope instability between February and April 2016; the G5S slope instability throughout 2017). The Burgers model has the form:

$$\mu = -Ae^{-Bt} + Dt + C \quad (32)$$

with the derivative:

$$\frac{d\mu}{dt} = ABe^{-Bt} + D \quad (33)$$

Where $A$, $B$, $D$, and $F$ are constants, or, in rheological terms:

$$\mu = \frac{\sigma}{\eta_m} t + \frac{\sigma}{E_k} \left(1 - e^{-\frac{E_k t}{\eta_k}}\right) \quad (34)$$

with the derivative:

$$\frac{d\mu}{dt} = \frac{\sigma}{\eta_m} + \frac{\sigma}{\eta_k} e^{-\frac{E_k t}{\eta_k}} \quad (35)$$

Where $\sigma$ represents stress, with units of psi, $\eta_m$ and $\eta_k$ represent Maxwell and Kelvin viscosities, with units of N*days/m$^3$, and $E_k$ represents Kelvin elasticity, with units of N/m$^3$. Visually, the Burgers model almost perfectly matches the slope’s displacement behaviour (Figure 76), with an average $R^2$ of 1.0. When fitting models to only the first half of each deformation event, the models still quite closely resemble the data, with an average predictive $R^2$ of 0.96 (Figure 77). The behaviour indicated beyond the range of fitted data appears reasonable.
The derivative model agrees well with the velocity behaviour of the slope, with an average $R^2$ of 0.87, and an average predictive $R^2$ of 0.75.

The physical basis for the steady-state velocity attained between deformation events is unclear. Intuitively, the pit slope should reach a velocity of zero as $t$ approaches infinity because the slope gradient reduces with increased deformation, and should reach equilibrium as the stresses driving movement equal the stresses resisting movement. The steady-state velocity observed in the data may be an artifact of active mining excavation between blasts.

5.4.4. Application of the Fractional Maxwell model to slope deformation

The Fractional Maxwell model has only recently been used to model rock creep (Ding et al., 2017) with experimental data from laboratory tri-axial testing, although similar fractional models have been investigated in salt rock creep modelling (Zhou et al., 2013).

To simplify regression, the Fractional Maxwell equations are modified as follows:

- Setting $\sigma / E$ to zero, because displacement is reset to zero at the start of each deformation event as part of the data pre-processing.

- Setting $A$, deformation event magnitude, as $A = \frac{\sigma}{\eta \alpha}$, with units of cm/day.

These simplifications result in the following equations, which have only two regression constants: $A$ and $\alpha$.

\[
\mu = \frac{At^\alpha}{\Gamma(1+\alpha)} \quad (36)
\]

\[
\frac{d\mu}{dt} = \frac{\alpha At^{\alpha-1}}{\Gamma(1+\alpha)} \quad (37)
\]

Visually, the Fractional Maxwell model agrees closely with the slope displacement data and has an average $R^2$ of 1.0. The predictive fits also show very strong agreement with slope displacement, with an average $R^2$ of 0.97. The $R^2$ values
for the velocity and predictive velocity fits are very high, with averages of 0.80 and 0.75 (Table 6).

5.4.5. **Summary**

The rheological models tested show good agreement with displacement data from deformation events (Figure 76), and the derivative models show good agreement with velocity data (Figure 78). Fits developed using only the first half of the deformation event datasets as input reveal that the Burgers and Fractional Maxwell models perform well as predictive tools (Figure 77 and Figure 79). These models generally show reasonably realistic behaviour outside of the range of fitted data.

Of the three rheological models tested, the Kelvin-Voigt model, which is the most frequently cited and used rheological model for time-dependent open pit slope behaviour, has the lowest average $R^2$ in each type of fit (displacement, velocity, predictive displacement, and predictive velocity). The Burgers model and the Fractional Maxwell model are the best-performing models for displacement and velocity fitting and display similar predictive performance.
Figure 76. Rheological fits to displacement for four deformation events.

Figure 77. Predictive rheological model fits to displacement for four deformation events.
Figure 78. Rheological fits to velocity for four deformation events.

2015-10-13

Kelvin – Voigt $R^2 = 0.74$
Fractional Maxwell $\hat{R}^2 = 0.83$
Burgers $R^2 = 0.95$

2015-12-04

$R^2 = 0.8$
$\hat{R}^2 = 0.95$
$\hat{R}^2 = 0.94$

2016-02-15

$R^2 = 0.78$
$R^2 = 0.91$
$\hat{R}^2 = 0.92$

2016-03-23

$R^2 = 0.35$
$\hat{R}^2 = 0.46$
$\hat{R}^2 = 0.4$

Figure 79. Predictive rheological fits to velocity for four deformation events.
5.5. **Conclusions**

Three empirical and three rheological creep models were compared for 24 deformation events, where the pit slope deformed in response to mining activity. Empirical models tested include the quadratic/linear model to provide context, the widely-used logarithmic model, and three orders of the recently-proposed Mercer polynomial model. Rheological creep models tested include the Kelvin-Voigt model, which is equivalent to models proposed by Martin (1993) and Broadbent and Ko (1971) to represent the mining-event deformation response, the Burgers model, which allows for steady-state creep, and the Fractional Maxwell model.

Models were tested by curve fitting regression to displacement data, deriving the velocity fit, and then calculating $R^2$ values between the fits and data. This process was repeated by performing regression only on the first half of each mining-event dataset to develop ‘predictive $R^2$’ values, which provide an indication of how well-behaved and useful each fit is beyond the range of fitted data.

Results (summarized in Table 6 and Figure 80) show that tested models closely fit displacement but have much more varied $R^2$ values for velocity. The Mercer polynomial and Burgers models show the closest fit to the data. Limiting regression to the first half of each dataset reveals that the Mercer polynomial models have very poor predictive $R^2$ values, indicating that complex polynomials may over-fit the data and exhibit unrealistic behaviour outside of the fitted range. The empirical models perform poorly when fit to a partial dataset and have low predictive $R^2$ values.

Considering both $R^2$ and predictive $R^2$, the Burgers and Fractional Maxwell models best describe the data and are most useful in prediction. The Kelvin-Voigt model is the poorest-fitting rheological model, but still out-performs the empirical models. Of these models, the Fractional Maxwell model will be used in following Chapter to investigate how the fitted rheological constants change with repeated deformation events as it performs similarly to the Burgers model, but has only two regression constants as opposed to three constants for the Burgers model.
Table 6. Goodness of fit: summary for tested models

<table>
<thead>
<tr>
<th>Model</th>
<th>Min. Parameters</th>
<th>R²</th>
<th>Predictive R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quadratic</td>
<td>2</td>
<td>0.99</td>
<td>0.55</td>
</tr>
<tr>
<td>Logarithmic</td>
<td>2</td>
<td>0.95</td>
<td>0.69</td>
</tr>
<tr>
<td>2nd Order Polynomial</td>
<td>4</td>
<td>0.99</td>
<td>0.69</td>
</tr>
<tr>
<td>3rd Order Polynomial</td>
<td>5</td>
<td>1.00</td>
<td>0.86</td>
</tr>
<tr>
<td>4th Order Polynomial</td>
<td>6</td>
<td>1.00</td>
<td>0.86</td>
</tr>
<tr>
<td>Kelvin-Voigt</td>
<td>2</td>
<td>0.99</td>
<td>0.75</td>
</tr>
<tr>
<td>Burgers</td>
<td>3</td>
<td>1.00</td>
<td>0.87</td>
</tr>
<tr>
<td>Fractional Maxwell</td>
<td>2</td>
<td>1.00</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Figure 80. Goodness of fit: summary for tested models
Chapter 6.

Investigating the Factors Controlling Pit Slope Deformation Behaviour Using the Fractional Maxwell Rheological Model

6.1. Introduction

The deformation of open pit slopes in response to mining events is thought to depend on several factors, including slope height, slope angle, structural geology controls, and rock mass quality (Martin, 1993; Mercer, 2006). Open pit slope deformation may also depend on other factors, including deformation history or strain; (Newcomen & Dick, 2015), the rate of mining, and blast size and proximity. The objective of this chapter is to investigate the deformation events for four pit slope case studies, using the Fractional Maxwell rheological model, and relate them to potential influencing factors.

Three previously-posed questions regarding successive time dependent deformation events (Mercer, 2006) are:

1. Can predictive characteristics be interpreted from time dependent deformation models?

2. How do the constants of the time-dependent curve fitting model change with time, slope height, and deformation history?

3. What factors influence pit slope creep rate?

These questions remain unanswered. Mercer (2006) developed an idealized mining event driven model (Figure 81), and developed several hypotheses related to the above questions. The hypotheses include a) over time and with mining of successive benches, the magnitude of deformation responses should increase b) the slope should require longer periods of time to return to steady state, as mining progresses and c) the idealized time and event dependent model is the same for each kinematic instability type. Mercer (2006) was unable to support these hypotheses, in part due to a scarcity of detailed, high resolution data.
Figure 81. Idealized time and event dependent deformation model for mined open pit slopes. Modified after Mercer, 2006.
A large dataset is required to investigate these hypotheses because a deforming pit slope is a complex system, involving an immense number of interacting blocks of rock, each of varying size, properties, and connectivity, intersected by geological structures. A deforming open pit slope is also a dynamic system, in which the geometry and stress states are constantly changing. As mining progresses deeper, the movement of the slope at any given time also changes the slope geometry and influences future slope behaviour. Even between mining events, the slope geometry and stress states change on a smaller scale as the pit slope strains over time. Because open pit slopes are complex and dynamic, the deformation response to a mining event will not depend upon a single parameter. However, with a large set of events, one can investigate general trends and correlations.

The time-dependent deformation model used in this chapter to fit each deformation event is the Fractional Maxwell model, a simple, well-performing model (Chapter 5.4) of the form:

\[
\mu(t) = \frac{A t^\alpha}{\Gamma(1+\alpha)} \quad (38)
\]

\[
\frac{d\mu}{dt} = \frac{\alpha A t^{\alpha-1}}{\Gamma(1+\alpha)} \quad (39)
\]

This model has two regression constants: A, a measure of the initial magnitude of the deformation of the event, and \( \alpha \), which reflects how gradually the velocity decreases after a mining event.

6.2. Methodology

To compare how deformation events change with time and in relation to other factors, the following steps are undertaken:

- Zones representative of the overall movement of each slope instability are selected, and pixels from slope monitoring radar data within those zones are averaged to develop deformation and velocity histories.
- Deformation events, which exist as ‘peaks’ in the velocity data, followed by a decrease in velocity, are extracted from each dataset.
- Regression (curve fitting) is applied to each deformation event using the Fractional Maxwell model.
• Constants derived from the regression curve are compared with variables to determine whether and how a variable correlates with a given constant

• Variables to be compared to the regression constants are determined from the spatial monitoring radar and the specific energy datasets.

6.2.1. Zone selection and pixel averaging

Pixels used to track each slope instability were selected by visually appraising the radar data, drawing a boundary around one or more representative sections of each of the instabilities, and filtering out data outside of these zones. Radar pixel measurements with coherence values less than 0.95, indicating a potentially unreliable measurement, were dropped from the analysis.

6.2.2. Mining event selection

Mining events are selected data points from peaks or spikes in the velocity data and extend to the lesser of a) three days after the peak and b) the next trough in the velocity data.

Peaks are selected using the PeakUtils Python library (Negri, 2017), which detects peaks by calculating the first order difference in a dataset. In addition to the input data (in this case: mean velocity over time), the user sets two parameters: threshold, and minimum distance. Threshold is a normalized value between 0 and 1, which sets the minimum amplitude for a peak to be detected (Figure 82 and Figure 83). Minimum distance sets the minimum distance between each detected peak; if multiple peaks within this minimum distance are detected, the algorithm selects only the peak with the highest amplitude.

The deformation responses to mining events are assumed to last for three days unless interrupted by another mining event. Should another mining event interrupt the response, a trough in the velocity data is formed (Figure 84), which is detected by performing peak detection on the additive inverse of the velocity data (i.e. -1*V).
Figure 82. PeakUtils peak selection using a threshold of 0.9999 and a minimum distance of 4 days

Figure 83. PeakUtils peak selection using a threshold of 0.05 and a minimum distance of 4 days
Figure 84. Examples of detected peaks (open circles with crosses) and troughs (small solid circles) in velocity

PeakUtils input parameters were chosen to over-select, rather than under-select peaks (mining events). This may add peaks that represent ‘noise’, rather than actual events. Erroneously identified events are filtered out in subsequent steps in the analysis by removing deformation events which have poor regression results (i.e. $R^2 < 0.5$; see example shown in Figure 85)
6.2.3. Slope deformation event regression

Regression is performed on the selected events using the curve-fitting function of the Scipy python library (Jones et al., 2001). The regression function used is the Fractional Maxwell model, where $A$ represents the magnitude of the event, and $\alpha$ represents the fractional viscosity of the movement, ranging from 0 (purely elastic behaviour) to 1 (purely viscous behavior). Fractional viscosity is closely related to how quickly the slope stops moving. If the slope stops moving almost immediately after the mining event, $\alpha$ is low, whereas if the slope gradually slows down, $\alpha$ is high. In simple terms, $A$ describes the size of the initial slope response, and $\alpha$ describes how quickly the slope returns to steady-state.

6.2.4. Blast pattern identification and characterization

Blast characteristics, such as blast size, location, and timing were identified as variables that could affect subsequent slope movement and therefore correlate with regression parameters. For example, given that larger blast patterns have the potential to cause greater changes in the stress state at the toe of slopes, larger blast patterns may correlate with higher magnitude deformation events. Detailed records of blast pattern size, timing, and geometry were unfortunately not made available for the current work.

Blast characteristics, including blast size (number of holes), location, and timing, were instead estimated from the specific energy dataset (Chapter 4). However, the specific energy dataset is a continuous list of all holes drilled over the history of mining in the Granite Lake Pit and does not include information regarding which blast pattern each
blast hole belonged to, or when the pattern was blasted. The specific energy dataset was therefore divided into individual patterns.

Individual blast patterns were identified by limiting the specific energy dataset to the region of interest, sorting the data by date and then by bench elevation, and then splitting specific energy into ‘patterns’ with boundaries defined by gaps in the drilling times and/or elevation. If drilling moved to another bench, the previously drilled holes are interpreted to belong to a finished blast pattern. Temporal gaps of greater than 12 hours between drilling of subsequent holes on the same bench are also interpreted as the start of a new blast pattern. This is because, on average, subsequent holes are drilled less than one hour (41.7 mins) apart. A time cut-off was added as after a blast pattern is drilled, the bench is blasted, and the drills shut down for the blast. The drills move to the start of the new pattern while digging occurs in the previously blasted location. Where this process results in identification of unrealistically large blast patterns (>300 holes), the division process is run again with a reduced temporal gap cut-off of three hours. Finally, identified patterns with a size of less than 25 holes are dropped from subsequent analysis. Example results from a blast pattern division process is shown in Figure 86.

This blast pattern division algorithm results in a list of blast patterns, with approximate size and location. It does not allow identification of the precise times blasts were initiated and resulted in a sometimes-noisy grouping. The times associated with each pattern reflect the time the final hole of the pattern was drilled, not the time the blast was initiated. The size (in number of holes) of each pattern may be a particularly noisy parameter. However, at a minimum, the proposed algorithm produces realistic patterns that show the bench elevation and location of active mining.
Figure 86. Blast patterns identified from the specific energy dataset shown as differently coloured points.

Figure 87 shows an example velocity plot from the G5N pit slope instability and indicates how identified velocity peaks (yellow stars) often occur at or near the time identified blast patterns are completed (purple dots). A red box is drawn to highlight a blast pattern that was completed at 10 pm on October 12, 2015; at 4 pm the following day, there was an abrupt spike in the slope radar velocity data. Figure 88 shows the location of this blast pattern and the spatial distribution of radar velocity averaged over the two days after movement started (October 13-15, 2015). Note the pit shell onto which velocity was interpolated is from October 31, 2015, so some of the blasted bench has already been mined away.

Figure 87. Comparison of the timing and size of identified blast patterns.
6.2.5. Pit slope instability geometry

Pit slope instability geometry is estimated from the minimum volume ellipsoid containing radar pixels within the broader instability area which are moving faster than 13 cm/day. The algorithm used to determine the geometry of the minimum volume enclosing ellipsoids is based on a Python implementation of MATLAB code described by Moshtagh (2005). This algorithm is an iterative optimization process, where an ellipsoid is generated, and its geometry is tested to see how well it contains all input points and how large its volume is. The ellipsoid geometry is varied to minimize the volume of the ellipsoid while retaining most of the points. Once the scores of subsequently tested ellipsoids are within a certain tolerance of one another, the calculation is completed.

Because minimum volume ellipsoids are calculated for such a large dataset (each two-hour timestep of radar data spanning years for multiple instabilities), this analysis uses a relatively high tolerance between successive ellipsoid estimates to limit calculation time. Because of this high tolerance, some points may lie just outside the calculated ellipsoid (Figure 89b), and the volume error in the ellipsoid can be up to approximately ten percent. However, a volume error of ten percent in the determined
ellipsoid corresponds with average radius errors of around two percent \((10^{1/3})\), which is small compared to other sources of error.

Occasionally, isolated pixels far from the main high-velocity cluster erroneously have velocities greater than 13 cm/day; these are filtered out at each time step using a custom filter based on the Statistical Outlier Removal (SOR) filter of the PCL library (Garage, 2017). The steps of the algorithm are:

1. Calculate the average and standard deviation of the distances between each point and its four nearest neighbors.

2. Remove points farther than the average distance plus one standard deviation.

This procedure removes points that are atypically far from their neighbours (see Figure 89).

![Figure 89. Example of minimum volume ellipsoid encompassing the G5N pit slope instability, generated a) before and b) after running a SOR filter.](image)

The results of the algorithm include the centroid of the slope instability, the longest, intermediate, and shorted radii \((r_3, r_2, \text{ and } r_1)\); see Figure 89), and the dip and dip direction of the instability, which is the pit wall orientation. Because oriented ellipsoids are generated, the radii do not perfectly correspond with a ‘height’ or ‘width’ of the slope instability, but in general, \(r_3\) is parallel to the dip of the slope and is half of the ‘length’ of the instability, and \(r_2\) is parallel to the strike of the slope and is ‘width’ of the instability. Because radar data only returns deformation from the surface of the pit slope,
the $r_3$ parameter does not correspond with the ‘depth’ of the instability and is not used. Example results from the G5N pit slope instability are shown in Figure 90.

![Deformation](image)

![Velocity](image)

![Ellipsoid geometry - raw data](image)

![Ellipsoid geometry - one day moving average](image)

**Figure 90.** Example results from minimum volume ellipsoid radius calculation for the G5N pit slope instability.

### 6.3. Review of pit slope instability case studies

The above methodology is applied to five instabilities (Figure 91; Table 7), to compare slope and mining characteristics with deformation behaviour. These include the G5NE Wedge (Figure 92), G5N (Figure 93), G5C (Figure 94), 10 Fault and G5S (Figure 95) slope instabilities.
Figure 91. Location of pit slope instabilities in the Granite Lake Pit.

Table 7. Pit slope instability summary.

<table>
<thead>
<tr>
<th>Pit slope instability</th>
<th>G5NE Wedge</th>
<th>G5N</th>
<th>G5C</th>
<th>10 Fault</th>
<th>G5S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total observed deformation (m)</td>
<td>10</td>
<td>20</td>
<td>18</td>
<td>58</td>
<td>76</td>
</tr>
<tr>
<td>Maximum size (m)</td>
<td>110 x 55</td>
<td>400 x 314</td>
<td>223 x 174</td>
<td>122 x 33</td>
<td>446 x 251</td>
</tr>
<tr>
<td>Height of instability (m)</td>
<td>122</td>
<td>229</td>
<td>229</td>
<td>122</td>
<td>274</td>
</tr>
<tr>
<td>Instability Mode</td>
<td>Wedge</td>
<td>Wedge</td>
<td>Toppling</td>
<td>Rock mass</td>
<td>Toppling</td>
</tr>
<tr>
<td>Number of structures</td>
<td>2</td>
<td>3</td>
<td>Unknown</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Structural complexity</td>
<td>Simple</td>
<td>Complex</td>
<td>Complex</td>
<td>Rock mass</td>
<td>Complex</td>
</tr>
<tr>
<td>Median specific energy (MPa)</td>
<td>42</td>
<td>55</td>
<td>53</td>
<td>36</td>
<td>41</td>
</tr>
<tr>
<td>Overall slope angle (°)</td>
<td>32°</td>
<td>30°-35°</td>
<td>33°</td>
<td>33°-36°</td>
<td>33°-36°</td>
</tr>
</tbody>
</table>
Figure 92. Photogrammetry of the G5NE Wedge slope instability showing a) uncoloured data, b) average velocity during June 2015, and c) specific energy data.
Figure 93. Photogrammetry of the G5N slope instability showing a) uncoloured data, b) average velocity during March 2016, and c) specific energy data.
Figure 94. Photogrammetry of the G5C slope instability showing a) uncoloured data, b) average velocity from October 2016, and c) specific energy.
Figure 95. Photogrammetry of the 10 Fault and G5S slope instabilities showing a) uncoloured data, b) average radar velocity from April 2017, and prism vectors and c) specific energy.
For the 10 Fault, G5C, and G5NE Wedge pit slope instabilities, a single zone of radar data was selected for analysis, as this appeared representative of the overall movement. For the G5S (Figure 96) and G5N (Figure 97) pit slope instabilities, two zones of radar data were selected: as discussed in Chapter 3, different sections of these slope instabilities appeared to behave differently.

Figure 96. Representative zones selected for analysis of the G5N pit slope instability.

Figure 97. Representative zones selected for analysis of the G5N instability.
6.4. Progression of deformation events over time

The following figures (Figure 98 to 104) show the main results of the analysis described above, including plots of deformation and velocity. The Fractional Maxwell regression parameters $A$ and $\alpha$, indicating the deformation event magnitude and fractional viscosity are also shown. The derived regression parameters are plotted with sizes scaled according to their coefficient of determination ($R^2$) values, which reflect how well the regression model fits the velocity data. Larger points indicate higher $R^2$ values. Regression parameters with $R^2$ scores of less than 0.5 are shown but are not included in subsequent analyses or when generating the fit lines. For context, the blasting bench elevation is included on the deformation event magnitude ($A$) vs. time plots.

Figures 98 to 104 to can be directly compared with the idealized model presented in Section 6.1 (Figure 81). Some differences are immediately apparent. Mercer (2006) hypothesized that the magnitude of deformation caused by mining events should increase with the height of the slope. The deformation event magnitude ($A$) versus time plots on Figure 98 through 104, show that for every slope instability, although the magnitude of events does increase with the slope height up to a certain mining depth bench, it then begins to decrease, even though the slope height continues to increase. In contrast, except for the G5NE Wedge slope instability, the fractional viscosity of the pit slope instabilities generally increases over time and does not return to pre-deformation levels possibly an indicator of cumulative damage within the pit slope instability with time.
Figure 98. Pit slope deformation, mining history, deformation events, and regression constants over time: G5NE_Wedge.
Figure 99. Pit slope deformation, mining history, deformation events, and regression constants over time: G5N.
Figure 100.  Pit slope deformation, mining history, deformation events, and regression constants over time: G5N_Wedge_1.
Figure 101. Pit slope deformation, mining history, deformation events, and regression constants over time: G5C.
Figure 102. Pit slope deformation, mining history, deformation events, and regression constants over time: 10 Fault.
Figure 103. Pit slope deformation, mining history, deformation events, and regression constants over time: G5S_Lower.
Figure 104. Pit slope deformation, mining history, deformation events, and regression constants over time: G5S_Upper.
6.5. **A comparison of change in predictors with observed slope behaviour**

The factors compared against the deformation event regression constants include deformation history, instability size, blast size, mining bench elevation, and distance between blasting and the instability centreline. The following sub-sections discuss specifically which parameters are investigated, how they are calculated, how they compare when correlated with either deformation event magnitude or fractional viscosity, and potential reasons for correlations.

6.5.1. **Pit slope deformation history**

Slope deformation history is selected as a potential predictor of future deformation response to mining events because as a rock mass deforms, different zones undergo strain, intact rock bridges break, and the rock mass quality decreases. That is, a rock mass accumulates damage as it undergoes strain. This damage may be localized along discrete structures, or it may be distributed along a zone. Notwithstanding, more damaged rock should clearly exhibit different deformation behaviour than less damaged rock.

Figure 105 shows an example of damage, or degradation in rock mass quality, with increasing deformation. Between March 15 and June 8, 2017, radar monitoring data recorded movements of over 46 m in some parts of the G5S pit slope instability. The March 15 photograph (Figure 105a) shows relatively clean benches and a fair quality rock mass, although poorer quality zones appear to cross-cut the area. By June 8, 2017 (Figure 105b), large blocks of intact rock have been reduced to rubble, benches are no longer distinguishable, and debris covers much of the slope. One would expect this dramatically changed slope rock mass to exhibit different slope deformation behaviour.
Deformation history can be measured using two metrics: accumulated deformation and strain.

Accumulated deformation is calculated as the total deformation a zone on the slope has experienced since the start of radar monitoring. Plotting fractional viscosity against accumulated deformation for each of the pit slope instabilities shows a clear albeit scattered relationship: as deformation increases, the slope deformation response is increasingly viscous, approaching a fractional viscosity of 1 (Figure 111). The G5NE_Wedge instability is the single exception to this. The G5NE_Wedge instability was a high velocity but short-lasting instability with few data points and low overall deformation and exhibits a brittle response. The regression lines shown are of the form $y$
\[ A \log(x) \], which reasonably approximate the data for each instability with the exception of the G5NE_Wedge instability.

Strain is calculated as the accumulated deformation divided by the length of the instability (specifically, two times the longest radius of the minimum volume ellipsoid, \(2 \times r_1\)). This definition of strain is similar to previous work (Newcomen & Dick, 2015) that defined strain as ‘the total movement measured at the surface divided by the height of the slope failure’. Areal strain, calculated as the accumulated deformation divided by the area of the instability (\(\pi \times r_1 \times r_2\)), was also calculated but areal strain vs. fractional viscosity showed a poorer correlation.

Strain could be a better predictor than ‘accumulated deformation’ because deformation distributed over a very large area should cause less concentrated damage than the same deformation limited to a small area. However, the fractional viscosity vs. strain relationships (Figure 112) are very similar to and have slightly poorer fits than the fractional viscosity vs. accumulated deformation relationships. Two possible reasons for this are:

1. A larger slope instability may exhibit a higher apparent fractional viscosity: a larger moving rock mass has more momentum, leading to a more gradual slowing following an event. If this is true, dividing deformation by length to calculate strain is dividing a variable that positively correlates with fractional viscosity by another variable that positively correlates with fractional viscosity, decreasing the strength of the original correlation.

2. True strain is typically unevenly distributed within the instability, and the length or area of the instability itself may therefore not be an appropriate denominator for calculating strain. For example, dividing the deformation of an instability by its length will greatly underestimate strain in the zone controlling movement if the instability is comprised of a large intact block is sliding on a basal sliding surface (Figure 106).
Fractional viscosity appears to increase as pit slope instabilities deform more and develop into masses of moving rock deforming along well-defined boundaries. The increase in fractional viscosity may reflect the decreasing shear strength of the instability slip surface over time (increasing slip surface damage). The instabilities are slower to return to equilibrium as less shear strength is mobilized. This may be caused by large-scale processes, such as the failure surfaces becoming more continuous, linear and smoother, and small-scale processes, such as shearing of asperities, breaking of intact rock bridges, and grinding up of gouge material along existing faults and newly developed shear surfaces and tectonic faults.

Consider the G5S slope instability, for example. The average fractional viscosity before late February 2017, when the western boundary (the lower-right of the figure) of the instability was a wide, jagged boundary (Figure 107a-c) was 0.74. After the boundary developed into a through-going structure (Figure 107d-f), the average fractional viscosity increased to 0.94, indicating that the slope instability behaviour became much less elastic and much more viscous.

If the shear strength along the slip surface of the G5S slope was decreasing with increasing strain, given that by March 2017 the slope was already so close to a factor of safety of 1, it is interesting that the pit slope did not experience catastrophic failure as deformation continued. One possible reason for this was that as the G5S slope was deforming, the overall slope angle was decreasing. It decreased from 35.6° in November 2016 to 33.3° in June 2017 (Figures 108 and 109). Geometry was changing in a manner...
that decreased forces driving the instability at the same time the rock mass was becoming more damaged and weaker.

Figure 107. Progression of the G5S slope instability over time.
The G5N slope instability had similar boundaries over its history of deformation and showed gradual increasing fractional viscosity from approximately 0.4 to 0.8. If this increase in fractional viscosity reflects a reduction in shear strength along the slip surface of the G5N slope instability, two causal mechanisms are the development and
increasing size of rear and lateral tension cracks (Figure 110), and small-scale degradation of material in and around GIB-2016-007 and 13 Fault.

![Figure 110](image)

**Figure 110. Photograph of the G5N pit slope instability taken on Jan. 27, 2016.**

This hypothesis also explains the initially viscous behaviour of the G5NE Wedge slope instability. In contrast to the two examples discussed above, where the instability slip surfaces appear to become more well-developed over time, and fractional viscosity increases over time, the wedge was already well-defined by very significant faults when it was daylighted. As it was daylighted it exhibited a higher fractional viscosity associated with low shear strength structures.
Figure 111. Fractional viscosity vs. accumulated deformation for each pit slope instability.
Figure 112. Fractional viscosity vs. strain for each pit slope instability.

Although the increase in fractional viscosity diminishes with accumulated deformation or strain, the impact of the increase in fractional viscosity on mining increases exponentially. The time required for a slope instability to return to a hypothetical safe mining velocity threshold of 10 cm/day is presented for the average magnitude deformation event in Figure 114. An event with a fractional velocity of 0.5 will cause a day of lost mining time; an event with a fractional velocity of 0.8 will cause a week of lost mining time; and an event with a fractional velocity of 0.85 will cause a month of lost mining time. Even regressive slope instabilities should be avoided, and if encountered, the cost of stepping in to reduce potential movements should be compared with potential costs of lost mining time.
The number of days required for a slope instability to return below a hypothetical safe mining threshold of 10 cm/day for the average deformation event (A=19 cm/day)

6.5.2. Rock mass strength and quality

The previous discussion shows how the deformation behaviour of individual slopes becomes more viscous as deformation and strain accumulates, and the slope rock mass becomes more damaged. Because damage reflects a reduction in rock mass strength, the more viscous behaviour of the slopes may be a result of a relationship between rock mass strength and viscosity. If this is the case, there may be a relationship between the slope deformation behaviour of the instabilities at low strain and the rock mass strength of those instabilities.

Although common measures of rock mass strength, such as the Hoek-Brown parameters, or even intact rock strength, such as UCS, are not available in numbers that would allow for meaningful comparisons between each of the slope instabilities, analysis of the specific energy data in Chapter 4 shows that specific energy has similar distribution to GSI or UCS approaching faults, and is a reasonable proxy for rock mass strength.

The specific energy for each of the pit slope instabilities was estimated by taking the mode of the distribution of specific energy data within 15 m of that instability. The ‘undamaged’ rheological (viscosity) behaviour of each instability was estimated by averaging the fractional viscosities from low-strain (less than one percent) deformation.
events. Limiting the fractional viscosity average to events early in the deformation history of each instability helps avoid comparing pre-damage strengths against post-damage slope behaviours.

Figure 114 shows the fractional viscosity vs. specific energy for each of the pit slope instabilities. For context, the fractional viscosity of an intact sandstone core sample as reported by Ding et al. (2017) is also presented. The data show an inverse relationship between fractional viscosity and rock mass strength: weaker rock masses exhibit a more viscous deformation behaviour than stronger, intact rock masses.

![Figure 114](image)

**Figure 114.** Average fractional viscosity vs. specific energy for slope instabilities at strains of less than 1%.

Given that specific energy *roughly* approximates GSI (Chapter 3), the best fit line in Figure 114 may provide conceptual insight into the changing character of the instabilities as they deform. For example, plotting the final fractional viscosities of the G5S_Lower and G5N instabilities (0.93 and 0.80) along the best fit line drawn in Figure 114 results in estimated specific energy values of 12 MPa and 29 MPa, respectively (Figure 115).
Figure 115. Specific energy for the G5S_Lower and G5N slope instabilities estimated from fractional viscosity, indicating the importance of progressive slope damage.

Plotting the change in specific energy values on the GSI chart (Figure 116) provides a conceptual indication of the change in material behavior before and after the G5N and G5S slope instabilities deformed by 20 m and 70 m, respectively. For the G5N slope instability, the inferred change in GSI is equivalent from moving from a blocky to very blocky rock mass, with fair to good surface conditions, to a blocky/disturbed/seamy rock mass with poor surface conditions. For the G5S slope instability, the change in GSI is equivalent from a block/disturbed/seamy rock mass with fair surface conditions to a laminated/sheared rock mass with poor to very poor surface conditions. This comparison is not meant to suggest a precise change in rock quality, but only to emphasize that the slope instability behaviour reflects an increase in damage and a decrease in rock mass quality as total deformation increases.
Figure 116. Chart for GSI estimates showing conceptual change in GSI inferred from fractional viscosity showing implications of progressive slope damage. Chart modified after Marinos and Hoek (2000).
6.5.3. Pit slope instability size

The size of a pit slope instability has been suggested to affect its deformation behavior (Mercer, 2006). A larger slope instability has more momentum than a smaller instability moving at the same velocity; perhaps larger instabilities therefore require more time to stop moving. Several parameters can be used to track slope instability size over time, including area, volume, width, and radius. For the current study, area and radius (half of the length of the instability), determined using the minimum volume ellipsoid calculation methods are used to measure size.

For most slope instabilities, both investigated measures of size, area (Figure 117) and r1 (i.e. half of the length of the slope instability; Figure 118) show almost no correlation with fractional viscosity. For most pit slope instabilities, the relationship is extremely scattered. For the analyzed zones in pit slope instability G5S, the correlation appears stronger, but it is not clear whether this implies that fractional viscosity is dependent on size. Because pit slope instabilities generally increase in size with time, and accumulated deformation also increases over time, the increase in fractional viscosity with size may be coincidental. The poor correlation observed between fractional viscosity and instability size may be a result of the correlation between deformation history and instability size (Figure 119).
Figure 117. Fractional viscosity vs. pit slope instability area.
Figure 118. Fractional viscosity vs. half of the pit slope instability length ($r_1$).
One parameter with the potential to influence slope response is blast size. Larger blasts (as measured by the number of holes in the blast pattern) should cause larger magnitudes of deformation in the slope for two reasons:

1. Blast hole spacing is generally constant, so a greater number of holes indicates a greater volume of rock blasted, which ceteris paribus should cause a greater stress change

2. Blast shockwave effects should be larger from a larger blast pattern.
Surprisingly, the magnitude of the slope deformation response (A) shows almost no correlation with blast size. This is true both for each individual pit slope instability and the combined dataset (Figure 120). This may suggest the algorithm used to identify and classify blast patterns may not be sufficiently accurate to capture realistic blast sizes. Or, it may be that the other variables contributing to the magnitude of the slope deformation response, such as structural geology, rock mass, and blast location overshadow the influence of blast size.

Figure 120. Slope deformation response magnitude vs. blast size (number of blast holes drilled).
6.5.5. Active mining bench

For an idealized structurally controlled instability, assuming rigid blocks divided by discrete large-scale faults, movement should only occur when critical faults (or fault intersections) daylight. Prior to and after daylighting the structure, no or limited slope deformation should occur. Comparing the deformation event dataset with the blasting dataset provides an opportunity to determine how closely real-world slope behaviour conforms to this simple idealized model.

Figure 121 shows the distribution of deformation events at different mining bench elevations in a violin plot, which combines box and whisker plots with an estimated frequency distribution of the data. The box and whisker plots show the second and third quartiles (the ‘interquartile range’) as a thick bar, the range of data as a thin bar (the ‘whisker’) and the median as a white dot. Around the box and whisker plots are the ‘vioins’, kernel density estimates of the distribution of the data. Like normal distribution curves, the violins are tallest where data are most frequent, and shorter where data are less frequent. Looking at the G5NE_Wedge pit slope instability in Figure 121, for example, shows a relatively tight distribution centred around 1234 m, with a median of 1234 m, and an interquartile range from 1234 m to 1250 m.

Figure 121 shows that for most pit slope instabilities, deformation events are clustered around certain active mining benches. However, in contrast to the hypothesis that deformation should only occur when critical structures daylight, deformation events span a range of active mining benches. The number of deformation events generally increases approaching a certain critical active mining bench (where structures or an intersection of structures daylights) and decreases as mining continues below this.
Figure 121. Distribution of deformation responses observed for different mining benches. Inset figures show a) G5N and G5NE_Wedge, with aerial photogrammetry coloured by specific energy, b) G5C, with aerial photogrammetry coloured by velocity, and c) 10 Fault and G5S on aerial photogrammetry coloured by velocity.
Figure 122 shows the same data visualized as a swarm plot, which shows the raw data counts (i.e. the number of deformation events), stacked to visualize distribution. The behaviour of the slope instabilities can be grouped into three categories. The G5NE_Wedge, which is the most structurally controlled instability, behaves closest to the idealized kinematic model: no deformation events occurred prior to mining the 1250 m bench. During blasting of the 1250 m bench, two deformation events are triggered. Four events occur at the 1234 m bench, then events cease completely as mining progresses below the 1234 m bench. The G5N and G5S pit slope instabilities, which are structurally controlled but more complex, show a progressive increase in the number of events approaching a certain bench (1143 m and 991 m, respectively), then a progressive decrease in events as mining continues below this bench. The G5C and 10 Fault slope instabilities, which have the least structural control show a much flatter distribution of events.

Figure 122. Swarmplot showing distribution of slope deformation responses observed for different active mining benches.

How tightly events cluster may be related to the structural control. The G5NE Wedge, which has the tightest distribution of events, is controlled by sliding along a simple wedge geometry. There were no deformation events until mining of the 1250 m
bench, which daylighted the 10 Fault (Figure 123). The G5N and G5S instabilities are also clearly structurally controlled (see Chapter 3) with a basal sliding plane (Fault 13 and 10 Fault, respectively) but are more complex and involve multiple structures. The G5C and 10 Fault slope instabilities, which do not have a single daylighting structure have the flattest event distributions.

![Figure 123. Example from the G5NE_Wedge slope instability showing where the critical structure for this instability daylights (approximately 1234 m).](image)

In addition to the increasing number of deformation events approaching certain benches, for the instabilities with a well-defined base, the average magnitude of the deformation events (i.e. $A$), and the percentage of blasts resulting in significant deformation events increases approaching the critical benches (Figure 124). Figure 124 combines multiple instabilities, each with unique structure and geometry, and is not meant to suggest an absolute relationship. Interestingly, although $A$ does increase approaching critical benches, the $A$ vs. distance correlation is very scattered. Factors other than vertical distance (e.g. complex interactions between blocks) must therefore have a stronger influence on deformation event magnitude.

The 10 Fault and G5C slope instabilities, which do not have a well-defined basal plane have a much flatter distribution, with a lesser increase in $A$ approaching the critical bench, and a percentage of blasts causing deformation events that depends less strongly on distance from a critical bench (Figure 125).
Figure 124. Deformation event magnitude and frequency approaching critical benches, for pit slope instabilities with a well-defined basal surface.
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Figure 125. Deformation event magnitude and frequency approaching critical benches, for pit slope instabilities lacking a well-defined basal surface.

6.5.6. Distance from the instability centreline

One predictor of how an open pit slope will respond to a blast could be the distance between the blast and the slope’s ‘centreline’ (Figure 126). Mining events
farther from the toe of the slope would be expected to have a lower impact on the instability.

Figure 126. The distance from centre concept, shown with G5S pit slope instability for reference.

Plotting the distribution of deformation events against distance from each instability centreline (Figure 127) shows that although the distributions for each instability cluster around the centreline, there is significant scatter and all the distributions are wider compared to the distributions around the different active mining benches (Figure 121).
Figure 127. The distribution of deformation events with distance from the pit slope instability centreline.

Plotting the deformation event magnitudes against distance from the centreline shows almost no relationship (Figure 128a), although the number and percentages of blasts triggering deformation events does increase close to the centreline (Figure 128b and Figure 128c). The scatter in the relationship may be exacerbated by spatial limitations in the comparison because blast patterns can be greater than a hundred metres wide, and the instabilities themselves can be hundreds of metres wide. A large blast at the corner of an instability may have an associated distance of over one hundred metres. Despite the scatter in the data, blasts far (>366 m) from instability centrelines did not trigger any deformation events.
The deformation behaviour of five pit slope instabilities was compared with deformation history, rock mass strength, instability size, blast size, active mining bench.
elevation, and the distance from instability using the Fractional Maxwell rheological model.

The regression constant $\alpha$, which describes the viscous behaviour of the pit slope movement, was compared with deformation history, rock mass strength as approximated using specific energy, and instability size. A relationship between $\alpha$ and deformation history was found for all the pit slope instabilities: as slopes deform and undergo strain, their deformation behavior becomes more viscous. At low strains, the slope instabilities in weaker rock masses (with lower specific energies) exhibit a more viscous behaviour than slope instabilities in stronger rock. The relationship between $\alpha$ and pit slope instability size is very scattered – although there may be a very weak correlation between instability size and $\alpha$, the data are inconclusive.

The regression constant $A$, which describes the magnitude of deformation events, was compared with blast size, active mining bench elevation, and distance between the centreline of the instability and the centre of the given blast pattern. Surprisingly, no relationship was observed between blast size and the resulting slope deformation, for individual instabilities or the combined dataset. The active mining bench was found to increase the deformation event magnitudes, the total number of major deformation events occurring, and the percentage of blasts that trigger major deformation events. As the pit slope is mined down approaching a primary structural control, deformation events increase in both magnitude and frequency. As the pit slope is mined past (and becomes farther from) the primary structural control, deformation events decrease in magnitude and frequency. A comparison of the deformation event magnitude and frequency with distance from the instability centreline showed a wide distribution. Overall, mining closer to the toe of the slope as expected has a greater impact on slope deformation. Blasts farther from instabilities are unlikely to cause a significant deformation response in the slope.

Each open pit slope, instability, and deformation event is unique. The strongest correlations found in this research still exhibit scatter and variability and predicting any given deformation event is difficult. However, some general trends are apparent:

- Fractional viscosity increases with deformation and slope damage, and at any given time the next slope deformation event is likely to be at least as
viscous as the previous event. Poorer quality rock will exhibit more viscous behaviour and require more time to fall below velocity thresholds.

- As mining approaches a critical structural control, one can expect to see an increase in the frequency and magnitude of major deformation events. If catastrophic failure is avoided when the structural control is daylighted, and mining continues below the structural control, one can expect to see a decrease in the frequency and magnitude of major events.

- The time and event dependent model is not, as previously suggested, the same for each kinematic instability type. The instabilities with stronger kinematic controls showed a much greater increase in frequency and magnitude of deformation events approaching those kinematic controls. The strongly structurally-controlled G5NE_Wedge instability, for example, has a tight distribution of major events across active mining benches: major slope deformation events only occurred over a two-bench interval, and only began when a major structure was daylighted. In contrast, the G5C pit slope instability, a toppling failure without a well-defined base, began as soon as the top of the instability was mined. Deformation events continued to occur over the mining of nine benches.
Chapter 7.

Summary and Recommendations for Future Work

7.1. Summary

Open pit slopes deform in response to mining. Slope stability radar and other techniques like UAV photogrammetry have provided an opportunity to interrogate the spatial and temporal distribution of that deformation in finer detail than previously possible. This thesis presents the results of an analysis of the deformation behaviour of five slope instabilities. Specific energy was investigated and found to be a useful tool to map and understand major faults and rock mass strength in the Granite Lake Pit, which is critical for understanding the pit slope instabilities. Five pit slope instabilities in the Granite Lake Pit were characterized and described using specific energy, UAV photogrammetry, and radar monitoring data. Three rheological and three empirical creep models were applied to 24 deformation events to determine which was most suitable for predicting and characterizing deformation behaviour; the Fractional Maxwell model was the best performing, simplest model. Mining and deformation events were identified from the entire radar monitoring dataset for each slope instability, and the Fractional Maxwell curve-fitting model was applied to each, so that the different regression parameters could be tracked over time and be compared with different factors such as deformation history and instability size.

7.1.1. A new method to map faults and rock mass strength distributions using specific energy

A highly variable specific energy dataset was provided by Gibraltar Mine. The dataset was cleaned to remove erroneous and outlying points, and then smoothed using a bilateral filter. The resulting point cloud showed clear planes of low specific energy that appeared to match faults from the 3D fault model provided by Gibraltar. Specific energy approaching the 10 Fault and 9 Fault were found to decrease similarly to RMR76. Then, geotechnical domain averages of specific energy were compared to design RMR and UCS values and found to correlate: geotechnical domains with higher RMR and UCS values also had higher specific energy values. A direct qualitative comparison of specific
energy and rock mass quality was completed by projecting specific energy onto UAV photogrammetry and comparing with ground-based LiDAR change detection data. Zones of higher quality rock with well-performing benches were associated with high specific energy, a minor fault was associated with reduced specific energy, and a major fault/rubble zone was associated with low specific energy. Based on these comparisons, a method was developed to project specific energy onto UAV photogrammetry and map faults from the resulting model.

Specific energy has a significant potential for understanding rock strength and structure. It can be collected automatically during blast hole drilling and is therefore an inexpensive data source covering everywhere mining has taken place. In contrast to expensive geotechnical drill hole data, which provides limited spatial coverage through an open pit, and UCS samples from those drill holes, which provide even less coverage, the quantity and coverage of specific energy data is outstanding. The disadvantages of specific energy are its high variability, size, and availability. Other than exploration holes, which are often drilled using different methods and may not have comparable specific energy results, limited data is available prior to mining. However, using the methods presented above, the high variability of the specific energy can be overcome with smoothing, and high data size can be made manageable by interpolating or projecting the data onto pit shells or photogrammetry data.

This thesis presents a novel, innovative, and straightforward method of mapping faults and characterizing rock mass quality in an open pit slope using specific energy data. To the author’s knowledge, this is the first instance of specific energy being utilized for fault mapping. This method, in combination with radar velocity maps and photogrammetry data has proven tremendously useful in understanding and characterizing the deformation behaviour of the pit slope instabilities in the Granite Lake open pit.

7.1.2. The Granite Lake open pit slope instabilities

Five slope instabilities at the Granite Lake open pit at Gibraltar Mine in central BC were investigated.
The G5NE Wedge slope instability is a relatively simple wedge failure in the northeast of the open pit controlled by the 10 Fault, GIB-2016-007, and the Derek Fault set. After the intersection of the 10 Fault and GIB-2016-007 was daylighted, significant deformation in the G5NE Wedge slope instability stopped.

The G5N slope instability is a large and complex wedge failure in the northeast of the open pit controlled by Fault 13 and GIB-2016-007. After the line of intersection between these faults was daylighted (i.e. after mining in the hanging wall of Fault 13 was completed), significant deformation in the G5N slope instability ceased.

The G5C slope instability is a toppling instability in the southeast of the Granite Lake pit. Several faults contribute to the instability, although none were previously mapped.

The 10 Fault slope instability is a zone of disintegrating, sloughing weak rock in the south wall of the open pit around one zone of the 10 Fault. This slope instability appears to be vertically constrained around the shallow-dipping 10 Fault, but may be exacerbated by lateral movements in the 10 Fault hanging wall.

The G5S slope instability is a complex instability in the south wall of the Granite Lake Pit. This slope instability is thought to involve toppling and is bounded by several faults, including the NFG fault, the 10 Fault, Fault 8, Fault 9, NF6, B2, and the Graben Fault. This instability began as two separate movements; near the crest of the slope, movement was occurring in a zone bounded by the NFG, Fault 8, and NF6. Movement was also occurring at the 10 Fault. After the 10 Fault was daylighted downslope of this instability, the two zones connected and became a single, larger instability.

The spatial velocity gradient was introduced as a new method of zoning slope instabilities and determining where strain is concentrated. Zones of high strain, or high spatial velocity gradient showed strong agreement with geological and gravity-induced faulting, cracks, and slope instability boundaries, and often also showed agreement with zones of low specific energy.
7.1.3. The application of different curve-fitting models to predict the short-term behaviour of open pit slopes

Three empirical and three rheological creep models were applied to 24 deformation events. Models were tested by performing curve fitting on displacement data, deriving the velocity fit, and then calculating $R^2$ values between the fits and data. This process was repeated by performing regression only on the first half of each mining-event dataset to develop ‘predictive $R^2$’ values, which provide an indication of how well-behaved and useful each fit is beyond the range of fitted data.

The empirical creep models poorly fit and predicted slope deformation and velocity data. Of the rheological models investigated, the Kelvin-Voigt model, which had previously been used to model open pit slope deformation responses, was notably the worst-performing. The Burgers and Fractional Maxwell models both performed well in fitting and predicting pit slope deformation and velocity. The Fractional Maxwell model, which has two regression parameters, is significantly simpler than the Burgers model, which has three. Therefore, the Fractional Maxwell model was chosen as the model to apply to each of the slope instabilities.

This research represents the first application of the Burgers and Fractional Maxwell rheological models to time-dependent pit slope deformation events, and the first evaluation of the suitability of different rheological models. The Fractional Maxwell model was found to be effective at predicting short-term slope deformation in the absence of new triggering events, and may be useful for estimating when a slope will slow to below alarm thresholds.

7.1.4. Investigating the factors controlling pit slope deformation behaviour using the Fractional Maxwell rheological model

Martin (1992) and Mercer (2006) recommended that curve fitting models be applied to a series of regressive events to track deformation behaviour over time, and determine whether behaviour is related to instability size, failure mode, geometry, or material properties such as rock mass strength.

This thesis represents the first time a rheological model has been used to fit and describe the deformation behaviour of open pit slopes as they’ve developed over time. In
The Fractional Maxwell rheological model was fit to nearly 200 deformation events from five detailed pit slope instability case histories, calculating the regression parameters $\alpha$, the fractional viscosity of the response, and $A$, representing the initial magnitude of the response, for each event. The deformation behaviour of the pit slope instabilities as described by these parameters was compared with deformation history, rock mass strength, instability size, blast size, active mining bench elevation, and the distance from instability. The fractional viscosity of the response varied with deformation history and rock mass strength. The magnitude of the response varied with active mining bench, but more than that, the number of significant responses, and the percentage of mining events triggering an event was strongly dependent on active mining bench for slope instabilities with a controlling basal surface.

Fractional viscosity increased with increasing deformation and had an inverse relationship with rock mass strength. More damaged slip surfaces exhibited higher fractional viscosities, and weaker rock masses exhibited higher fractional viscosities. These findings suggest that, in the Granite Lake open pit, fractional viscosity is related to the shear strength along the slip surface. Fractional viscosity did not appear to significantly vary with instability size.

The variance of the initial magnitude of the deformation response, $A$, with location, suggests that this parameter may be related to the magnitude and location of the stress change with respect to the slope instability. Where mining caused a large stress change near a basal surface or near where wedge intersections daylighted, the instability was more likely to exhibit a significant deformation event, and that deformation event had a higher average magnitude. The likelihood of a significant deformation response occurring, and the magnitude of that response, was less dependent on active mining bench for slope instabilities without a controlling basal surface. No relationship was found between estimated blast size and magnitude of the deformation response; this surprising finding may indicate only that the method used to estimate blast size requires improvement.

The time and event dependent deformation behaviour is not the same for each kinematic instability type as previous work (Mercer, 2006) suggested. The instabilities with basal boundaries showed a much greater increase in frequency and magnitude of deformation events as the kinematic control was approached. The strongly structurally-
controlled G5NE Wedge instability, for example, has a tight distribution of major events across active mining benches: major slope deformation events only occurred over a two-bench interval, and only began when mining occurred near where a major structure would daylight. In contrast, the G5C pit slope instability, a toppling failure without a well-defined base, began as soon as the top of a zone of foliated rock was mined. Deformation events continued to occur at a similar rate over the mining of nine benches.

### 7.2. Conclusions

Prior to slope acceleration and collapse, open pit slopes exhibit regressive deformation events that occur following blasts and changes to the stress state. These events provide insight into how slopes are behaving and how they will behave as mining continues. This work summarizes an investigation of the regressive deformation behaviour events from five slope instabilities in the Granite Lake Pit at Gibraltar Mine, and concludes that:

- The Fractional Maxwell model is the most suitable and simplest rheological model for describing regressive pit slope behaviour. This model allowed comparison of the resulting regression constants over time and with other factors. Although the Fractional Maxwell model can accurately model and predict short-term deformation, it is a model that fits conditions at a certain time; when conditions change, previously calculated regression parameters will no longer describe behaviour. In cases like the G5S, movement was so significant that the overall slope angle became two degrees shallower.

- At the Granite Lake Pit, geological structures are paramount in the both the development of slope instabilities and in how the slope instabilities respond to continued mining. None of the slope instabilities would have developed without the influence of faulting. When slope instabilities were moving along a basal structure or intersection of structures, they became less active and stopped moving after it was daylighted.
• None of the instabilities investigated developed without warning. In each case, the instabilities exhibited significant regressive deformation events at least one bench prior to exhibiting peak deformation activity.

• Although regressive instabilities can be managed, they should be avoided, and when encountered, deformation should be minimized when possible. Increasing deformation causes increases in fractional viscosity, which can cause exponential increases in lost mining time. Proactive actions to minimize deformation may therefore be cost effective even if the actions (for example a step-in or change to geometry) cause ore to be sterilized.

• Previous guidelines regarding whether a slope is in a state of progressive or regressive instability include:

  “…a displacement rate above 5 cm/day usually indicates that a failure is in the progressive stage and that total collapse could occur within 0 to 48 days” (Zavodni, 2000)

  “Movement rates in excess of 10 mm/day up to 100 mm/day or more are indicative of progressive failure.” (Martin, 1993)

  Given these authors’ definition of ‘progressive’ slope instability, which is a slope exhibiting long-term acceleration, such guidelines are obsolete. Firstly, higher frequency radar and prism monitoring data show that for brief periods following a blast, an instability can reach a velocity of nearly 200 cm/day while still exhibiting regressive behaviour, contradicting these guidelines. Secondly, modern monitoring methods facilitate identification of whether a slope is accelerating or decelerating, eliminating the need for such guidelines, the first of which was developed during a time when some mines monitored pit slope deformation monthly (Martin, 1993). A slope instability exhibiting increasing velocity is in a progressive stage; an instability exhibiting decreasing velocity is in a regressive stage.

• A fractional viscosity of one is equivalent to a factor of safety of one, and a slope with a fractional viscosity of one will continue moving until conditions change. Whether or not a slope instability progresses to collapse appears to be dependent on how the slope geometry and shear
strength changes with deformation. The G5S slope instability experienced strain and damage sufficient to increase fractional viscosity to approximately one, but at the same time it was deforming in such a way that the overall slope angle was becoming shallower over time. If deformation was occurring such that the instability geometry was becoming more prone to failure, or maintained the same geometry, the instability may have accelerated to catastrophic failure because of the accumulating damage along the failure surface.

- Fractional viscosity may increase with deformation because the faults and slip surfaces bounding a slope instability become more well developed, and damage allows connection of previously unconnected discontinuities, decreasing shear strength.

7.3. **Recommendations for future work**

Although a great quantity of data was considered in this study, some important datasets were not available. These include continuous groundwater data local to the slope instabilities, and a detailed blasting record. Future research should investigate how the Fractional Maxwell regression parameters vary with groundwater pressures in open pits. The blasting record estimated from the blast drill hole database was sufficient to link displacement events with certain benches and locations, but two important parameters were uncertain: the precise time of blasting, and the blast size. A precise knowledge of the timing of blasts could reduce the scatter in the relationship between blast location and the resulting deformation response, and a better record of blast size will allow improved testing of the relationship between blast size and the resulting deformation event.

Further research could expand upon and further develop the work above. The following research approaches are recommended:

- Although the relationship between specific energy and rock mass strength is sufficient to map faults and qualitatively describe rock mass strength, a more direct comparison between specific energy and rock mass strength should be undertaken to better understand and rigorously quantify this relationship.
Currently, it is unclear if specific energy can be compared across lithologies and mines, and it is unclear if specific energy is directly linked to rock mass strength or indirectly linked through intact strength. The influence of jointing intensity and orientation is also unclear. A better understanding of specific energy and its relationship to other parameters could be achieved by performing GSI bench or window mapping in one or more open pit slopes and comparing the results to specific energy on a window by window basis.

- It is essential that curve fitting using the Fractional Maxwell model should be performed using monitoring data at other mines and open pits, and the resulting regression parameters compared with strain, rock strength to validate and build upon the findings of this research. A rheological slope performance database should be built based on ground radar monitoring at a variety of open pit rock slopes to allow the results of this research to be optimized and advanced.

- The above investigation of the factors controlling pit slope deformation compares parameters across pit slope instabilities using subjectively selected zones. Different zones within individual instabilities should be analysed and compared to determine how sensitive analyses are to zone selection, and to develop guidelines to select representative zones.

- The use of other time-dependent damage models (such as the SUVIC model) should be explored.

- Numerical modeling should be performed to further investigate factors that influence fractional viscosity and the magnitude of pit slope deformation responses. A User defined constitutive Fractional Maxwell creep model should be developed and used to constrain future open pit numerical models against ground-based radar monitoring.

- Future consideration should be given to combining ground-based radar (with detailed structural geology investigations), in-slope borehole instrumentation and microseismicity monitoring to constrain rheologic surface behavior recorded by radar against internal changes within the rock mass.
References


Appendix A.

Curve Fitting Dataset
Figure A1. Quadratic fits to displacement (black) and velocity (red).
Figure A2. Quadratic fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.
Figure A3. Logarithmic fits to displacement (black) and velocity (red).
Figure A4. Logarithmic fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.
Figure A5. 2nd order polynomial fits to displacement (black) and velocity (red).
Figure A6. 2nd order polynomial fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.
Figure A7. 3rd order polynomial fits to displacement (black) and velocity (red).
Figure A8. 3rd order polynomial fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.
Figure A9. 4th order polynomial fits to displacement (black) and velocity (red).
Figure A10. 4th order polynomial fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.
Figure A11. Kelvin-Voigt model fits to displacement (black) and velocity (red).
Figure A12. Kelvin-Voigt model fits to displacement (black) and the velocity (red), fitting only to the first half of each dataset.
Figure A13. Burgers model fits to displacement (black) and velocity (red).
Figure A14. Burgers model fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.
Figure A15. Fractional Maxwell model fits to displacement (black) and velocity (red).
Figure A16. Fractional Maxwell model fits to displacement (black) and velocity (red), fitting only to the first half of each dataset.