Relationship between Particle Size Distribution and Porosity in Dump Leaching

by

Shuo Zhang

B.Sc, The University of Waterloo, 2015

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Applied Science in The Faculty of Graduate and Postdoctoral Studies (Materials Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA (Vancouver)

October 2017

© Shuo Zhang, 2017
Abstract

Fluid flow is a critical process involved in the valuable metals extraction from low grade ore in heap and dump leaching as well as the release of harmful substances from waste rock piles. The mechanisms by which fluids move through the porous media depend on the fluid properties and the intrinsic properties of the porous media, with permeability being one critical factor. Particle size distribution is a key factor that affects permeability by forming pores of different structure and size. The objective of this research was to assess the particle size distribution in heterogeneous packed ore/rock beds and quantify the effect of particle size distribution on porosity. In the studied mine site, the particle size distribution in the dump leach pad was determined by analyzing aerial images of multiple dump faces taken by a drone. Particles spanned a wide range in size from less than 2 cm in diameter to larger than 2 m in diameter, with a $P_{80}$ to be 2 m. The spatial segregation of fine particles and coarse particles along the dump faces was observed, which may contribute to the formation of preferential flow.

The effect of particle size distribution on porosity was quantified by two methods: the bulk density and CT-imaging techniques. Porosities under three particle sorting conditions were studied: narrow-sized particles, poorly sorted particles and well sorted particles. For narrow-sized particles, the porosity measured by the bulk density method decreased as the particle size was increased up to 0.151 mm after which the porosity remained constant in the range tested. The influence of the particle size on the porosity for the well sorted particles was similar to that of the narrow-sized particles from both of the methods. For poorly sorted particles, in both methods, porosity decreased as the fraction of the fine particles added was increased to a certain value, after which the porosity started to increase as the fraction of fine particles was further increased. The results have important implications for metal extraction from run of mine ores using dump leaching and release of contaminants from waste rock piles by influencing fluid flow properties.
Lay Summary

The motivation of this study was to quantify the effect of particle size distribution on the behavior of fluid flow. Fluid flow plays a key role in the determination of extraction efficiency in dump and heap leaching. Particle size distribution is an easily obtained parameter that influences fluid flow by influencing the shape and size distribution of the pores and thus the permeability. Hence, the research objectives were to quantify particle size distribution and its effect on porosity. The findings of this study showed that preferential flow could occur in heap and dump leach pads, and emphasized the effect of particle size distribution on flow behavior. The results may contribute to the optimum design of leaching pads to improve metal extraction efficiency.
Preface

Table of Contents

Abstract .......................................................................................................................... ii
Lay Summary ................................................................................................................ iii
Preface ........................................................................................................................... iv
Table of Contents ........................................................................................................... v
List of Figures ................................................................................................................ viii
List of Tables ................................................................................................................ vii
Acknowledgement ....................................................................................................... x

Chapter 1. Introduction ................................................................................................. 1
  1.1 Research Context ................................................................................................. 1
  1.2 Significance of the Research .............................................................................. 1
  1.3 Research Objectives ......................................................................................... 2

Chapter 2. Literature Review ...................................................................................... 3
  2.1 Fluid Flow and the Mechanisms ....................................................................... 3
    2.1.1 Pore scale .................................................................................................. 4
    2.1.2 Darcian Scale ............................................................................................ 5
    2.1.3 Areal Scale ............................................................................................... 7
    2.1.4 Comparison of the Scales ......................................................................... 8
  2.2 Correlative Parameters about Fluid Flow ......................................................... 9
  2.3 Permeability and the Approximation ................................................................. 12
  2.4 Measurement of Particle Size Distribution ....................................................... 16
    2.4.1 Sieve Analysis ........................................................................................... 17
    2.4.2 Image Analysis .......................................................................................... 18
  2.5 Measurement of Porosity .................................................................................. 19
    2.5.1 Definition of Porosity ............................................................................... 19
    2.5.2 Measurement of Porosity ......................................................................... 21
  2.6 Summary .............................................................................................................. 22

Chapter 3. Particle Size Analysis Using Aerial Image Processing ............................ 23
  3.1 Introduction ......................................................................................................... 23
  3.2 Methodology ....................................................................................................... 23
    3.2.1 Image Acquisition ..................................................................................... 23
    3.2.2 Image Processing ...................................................................................... 24
    3.2.3 Statistical Interpretation of Results ......................................................... 25
    3.2.4 Possible Inaccuracy Caused by Image Quality ........................................ 26
  3.3 Results and Discussion ....................................................................................... 26
Chapter 4.  Porosity Analysis using the Bulk Density and CT Imaging methods

4.1 Introduction

4.2 Methodology

4.2.1 Experimental design

4.2.2 Sample Preparation

4.2.3 Experimental Procedures

4.2.4 Possible Inaccuracy

4.3 Results and Discussion

4.3.1 Relationship between Porosity and Particle Size Distribution for Narrow-sized Particles

4.3.2 Relationship between Porosity and Poorly Sorted Particles

4.3.3 Relationship between Porosity and Well Sorted Particles

4.3.4 Relationship between Porosity Distribution and Particle Size

4.4 Conclusion

Chapter 5.  Conclusions and Future Work

Reference
List of Tables

Table 2-1 Scales, Conceptual Models, Critical Parameters, and Measurements Relevant to Flow Mechanisms in the Vadose (Hendrickx et al., 2005) ................................................................. 9
Table 2-2 Typical Porosity Values of Natural Sedimentary Materials (Bear, 2013) ................. 20
Table 4-1 Narrow Sized Samples Size .................................................................................. 35
Table 4-2 Components of Poorly Sorted Samples ................................................................ 36
Table 4-3 Components of Well Sorted Samples ..................................................................... 36
Table 4-4 Specimen size and the corresponding sample holder size in CT scanning .......... 38
List of Figures

Figure 2-1 Schematic showing different preferential flow mechanisms observed at pore and Darcian scales (Hendrickx et al., 2001) ................................................................. 8
Figure 2-2 Schematic showing different preferential flow mechanisms observed at the areal scale (Hendrickx et al., 2001) ................................................................................................. 9
Figure 2-3 Darcy’s Experiment Set up (Bear, 2013) .............................................................................. 10
Figure 2-4 Sieving curves for (A) glass beads and (B) sands in a 50-mesh square wire sieve. Both of the samples have the same nominal mass of 110 g (Aslan et al., 1998) ................................. 18
Figure 2-5 Dead-end pores (Bear, 2013) .................................................................................................. 20
Figure 2-6 Experimental setup based on the Boyle-Mariotte’s gas law (Bear, 2013) .................. 22
Figure 3-1 Schematic for dump construction via truck end dumping and the setup for the image acquisition (left); a drone in the process of acquiring images of the leach pad at the case study mine (right) ........................................................................................................ 24
Figure 3-2 An example of a calibrated image of a dump face (left); the corresponding binary image after edge detection and image thresholding (right) ................................................................. 27
Figure 3-3 Particle size distribution derived from the four images representing the four distinct dump faces ........................................................................................................................................... 27
Figure 3-4 Particle size distribution from the sieve analysis in the fine particle range from 0.01 cm to 20 cm (A); Combination of particle size distribution derived from the sieve analysis and the image analysis (B) ........................................................................................................ 28
Figure 3-5 Particle size distribution along different dump faces at different depths from the top to the toe. Different lines represent different dump faces being analyzed ........................................................................................................ 29
Figure 3-6 Characteristic diameters: d_{10}, d_{50} and d_{80}, with the error bars representing the standard deviations from all sub images for a particular depth (left); Uniformity coefficient and coefficient of gradation, along the dump face from the top to the toe (right) .................................................................................. 30
Figure 3-7 Change of Sauter mean diameter at different depths (left); Estimation of the dump permeability with increasing depth (right) ........................................................................................................ 32
Figure 4-1 Experiment apparatus designed for the bulk density measurement .......................... 35
Figure 4-2 Scanco Medical µCT100 (http://www.phenogenomics.dentistry.ubc.ca/equipment/MicroCTSpecimenScanner/) .............................................................. 36
Figure 4-3 Clear crush drain rocks (http://www.artsnursery.com/page/bulkgravelrock) ................ 37
Figure 4-4 The relationship between porosity and narrow particle size under loose random packing (left) and close random packing (right) derived from bulk density .................................... 42
Figure 4-5 8-bit binary image of the cross section of the samples consisting of narrow-sized particles in 2.19 mm after calibration and thresholding (left); the relationship between porosity and narrow particle size under close random packing derived from CT imaging (right) ............ 43
Figure 4-6 Comparison of porosity of narrow size particles derived from bulk density and CT imaging .......................................................................................................................... 43
Figure 4-7 The relationship between porosity and poorly sorted particle size under close random packing derived from bulk density ................................................................. 44
Figure 4-8 8-bit binary image of the cross section of the samples consisting of poorly sorted size particles with 50% 0.2135 mm & 50% 2.19 mm after calibration and thresholding (left); the relationship between porosity and the fraction of poorly sorted particle size under close random packing................................................................. 45
Figure 4-9 Comparison of porosity of poorly sorted size particles derived from bulk density and CT imaging ........................................................................................................................................ 46
Figure 4-10 Porosity of well sorted particle derived from bulk density (left); Comparison between porosity of well sorted particles derived from bulk density and CT scanning (right).... 47
Figure 4-11 Comparison of porosity of narrow-size particles and well sorted particles derived from bulk density (left); Comparison of porosity of narrow size particles and well sorted particles from CT imaging (right) ........................................................................................................................................ 48
Figure 4-12 CT images of the cross section of one sample in size 2.19 mm at different positions ............................................................................................................................................... 48
Figure 4-13 CT images of the cross section of a poorly sorted sample consisting of 25% 0.2135 mm particles and 75% 2.19 mm particles at two vertical positions (left) and a well sorted sample made up of 25% 1.595 mm, 25% 0.8535 mm, 25% 0.6035 mm and 25% 0.302 mm particles at two vertical positions (right) ........................................................................................................................................ 49
Acknowledgement

I offer my enduring gratitude to the faculty, staff and my fellow students at the UBC, who have support me and help me in the two-year study.

I owe particular thanks to my supervisor Dr. Wenying Liu, who has spent unremitting efforts on instructing me to study well and live with a healthy habit, and who has supported me both financially and mentally.

I thank Dr. David Dreisinger for the financial support.

I thank Dr. D. Dreisinger, Dr. R. Beckie, and Dr. W. Poole to be my committee member.

Special thanks are owed to my parents, who have supported me throughout my years of education, both morally and financially.
Dedication

To my parents
Chapter 1. Introduction

1.1 Research Context

Fluid flow is a critical process involved in the extraction of valuable metals from low grade ore in heap and dump leaching as well as the release of potentially harmful substances from waste rock piles (Lee et al., 2012; Wu et al., 2007). The movement of fluids through the packed ore/rock beds carries essential substances for chemical reactions and microbial activities to occur (Lasaga et al., 1993). Understanding the mechanisms by which fluids flow through the porous media is critical for optimizing the efficiency of metal extraction and minimizing the release of constituents of environmental concern.

The key property used to characterize fluid flow is the hydraulic conductivity, which, among other factors, depends on the permeability of the porous media (Cox et al., 2001). A relatively simple and straightforward way to estimate permeability is by particle size distribution, which affects permeability by forming pores of different structure and size (Marshall, 1958). To understand fluid flow properties in the context of dump leaching and waste rock piles, it is critical to examine the particle size distribution and build the relationship between particle size distribution and pore size distribution. Using dump leaching as the case study, the objective of this research was to determine the particle size distribution and quantify the effect of particle size distribution on the porosity of highly heterogeneous dump leach pads.

1.2 Significance of the Research

The mechanisms by which water and air flow through the unsaturated porous media, i.e., dump leach pads and waste rock piles, are determined by a series of parameters, including the characteristics of the fluid, the intrinsic properties of the ore grains making up the packed beds, and the geometric dimensions of the ore particles (Bear, 2013). The ease of fluid flows through the porous media can be described by the hydraulic conductivity that relates to the intrinsic permeability of the porous media, the degree of saturation, and the density and viscosity of the fluid (Alyamani et al., 1993). Among these factors, the permeability of the packed bed plays a key role in determining the paths and the velocity of the fluid passing through it.
Permeability is one of the most complex properties of the porous media because of the highly heterogeneous nature of the particles in the porous media. Grain size distribution is considered as the direct information that can be obtained in a relatively easy manner for permeability estimation (Stewart et al., 2006). Pore size distribution, which is intimately linked to the grain size distribution, is frequently involved in the determination of permeability. Hence, to understand the flow properties and eventually achieve optimum design of dump leach pads and waste rock piles, it is essential to firstly determine the particle size distribution and its effect on porosity.

1.3 Research Objectives

Using dump leaching as the case study, the general objective of this research is to determine the particle size distribution in the highly heterogeneous packed ore beds and build the relationship between particle size distribution and porosity. The two specific objectives are:

- **Determine the particle size distribution and spatial segregation of particle sizes in dump leaching.** Particle size distribution at the case study mine was derived by analyzing aerial image of multiple dumping faces taken during the construction of the dump. The results are reported in Chapter 3.

- **Quantify the effect of particle size distribution on porosity.** Three particle sorting conditions were studied in laboratory: narrow-sized, well sorted, and poorly sorted samples. Two methods were applied to measure porosity: the bulk density and the CT imaging techniques. The results are reported in Chapter 4.
Chapter 2. Literature Review

Fluid flow is a critical factor in controlling the metal extraction efficiency in heap and dump leaching. The movement of fluid carries reactants to and products from ore particle surfaces. (Wood et al., 1982). Fluid flow also plays a critical role in the release of potential harmful substances from mine waste materials. Thus, understanding the mechanisms of fluid flow and the factors affecting fluid flow is critical in the determination of metal extraction rate in heap and dump leaching, as well as the release of constituents of concern from waste rock piles (Da Pelo et al., 2009).

In this chapter, the mechanisms of fluid flow are reviewed in Section 2.1, and the parameters influencing the flow mechanisms are introduced in Section 2.2. Specifically, one factor that affects fluid flow is permeability. Empirical relationships for estimating permeability are introduced in Section 2.3. Key factors in the permeability estimation are the particle size distribution and the porosity of the porous media. Methods applied in the measurement of particle size distribution and porosity are summarized in Section 2.4 and Section 2.5. Finally, Section 2.6 summarized Chapter 2.

2.1 Fluid Flow and the Mechanisms

The stable supply of metals is of vital importance to the modern economy (Reck et al., 2012; Wu et al., 2007). Metal extraction from ores using heap and dump leaching have been regarded as a more environmentally friendly alternative to conventional methods used for the extraction of valuable metals (Cathles et al., 1975; Ghorbani et al., 2011). Dump leaching is used to extract valuable metals from ore of low quality and grade, tailings, and waste materials. The cutoff grade of the materials processed is determined by various factors (Wu et al., 2007). The packed ore beds are unconsolidated porous media that allow the solutions applied on top to penetrate through the packed material. The behavior of fluid movements in dumps plays a key role in determining metal extraction efficiency. It has been observed that fluid flow through porous media occurs in two ways: uniform (Green et al., 1911), and non-uniform (Lawes, 1882). The uniform flow leads to the stable wetting front parallel to the media surface, while the non-uniform flow leads to the irregular wetting of the soil. The non-uniform movement of the fluid causes the dissolved solutes to move along certain paths and bypass other parts of the porous
media. This phenomenon is denoted as preferential flow (Hendrickx et al., 2001). The preferential flow results from different mechanisms that often work simultaneously, so various flow patterns are formed. Three types of flow pattern are identified and models are developed to describe them: pore scale, Darcian scale, and areal scale.

2.1.1 Pore scale

Based on the concept of a fluid continuum filling the void space, flow pattern at the pore scale was established. It is only valid when the pore diameters are larger than the mean free path of the water molecules. The model related to the pore scale is mathematically described by the Navier-Stokes equations, (Hendrickx et al., 2001). Although most flow conditions in vadose zone meet the continuum requirement of the equations, only a few exact mathematical solutions exist because of the intricacy of the Navier-Stokes equations (Currie, 1993). The pore scale deals with the solutions represented by the Hagen-Poiseuille equation. For example, the water flux through the saturated parallel plates under laminar flow conditions can be described as

\[ q_{fr} = -K_{fr} \frac{dH}{dz} \]  

(Bear et al., 1993), where \( q_{fr} \) is water flux (m/s), \( K_{fr} \) is the hydraulic conductivity in the fracture (m/s), \( H \) is total hydraulic head (m), \( z \) is vertical distance (m). The hydraulic conductivity is defined as

\[ K_{fr} = \frac{\rho g b^2}{\mu 12} \]  

(Corey, 1994), where \( \rho \) is fluid density (kg/m\(^3\)), \( g \) is the acceleration due to gravity (m/s\(^2\)), \( b \) is the aperture opening (m), and \( \mu \) is the dynamic viscosity (kg/s · m).

Eq. 2.1 and Eq. 2.2 show that water flow through soils and rocks on the pore scale can be described using only the pore size. However, the materials suitable for this kind of description are limited because the pore structure of typical materials is complex in geometry. In such materials with complex pore structures, macropore flow often occurs, which is rapid water flow.
through macropores in fine-textured soils or media. In this case, water flows through paths with less resistance through macropores and bypass the denser parts of the material. Thus, a considerable fraction of the porous media is bypassed by the infiltrating water. Macropore flow occurs when a part of the porous media is saturated or close to saturation and the water entry potential of the macropore is exceeded.

The existence of macropore flow has been studied in many experiments, and some models related to preferential flow have been developed. For example, the hydraulic functions of three types of macropores under saturated condition were studies through the dye tracing tests (Bouma et al., 1977). Flow pathways of water in different soils and the effect of initial water content was investigated by dye-tracing experiments (Flury et al., 1994). Moreover, the theories of potential flow and boundary flow under unsaturated condition in structured soils was evaluated (Germann, 1990).

Another example was conducted by Forrer, and the spatial dispersion of the fluid inside the porous media under unsaturated conditions was quantified by tracer tests followed by image analysis technique (Forrer et al., 1999). Both low and high infiltration rates, 5 and 25mm/day were applied and leached into the soil, and the tracer plume was recorded vertically as images. The data from the images was analyzed in both horizontally and vertically, and was fitted into advection-dispersion models by adjusting corresponding parameters. The study illustrated that both vertical and horizontal concentration were significant in affecting the flow regime, and that boundary effects of sub-layers influence fluid flow.

Experiments demonstrate that fluid flows through some certain paths constructed by a small portion of particles (Germann, 1990). However, there still exists uncertainties regarding the relationship between the fluid flow mechanisms and the characteristics of the porous media.

2.1.2 Darcian Scale

Studying the fluid flow on the pore scale is tedious when the structure of the porous media is complex. Thus, a larger scale, Darcian scale, is applied (Hendrickx et al., 2005). Instead of considering geometries of pores, a volume consisting of void spaces and solid particles is used as the concept model in this scale (Hendrickx et al., 2001). At the Darcian scale, the relationship
between water flux in the vertical direction and the unsaturated hydraulic conductivity is represented by the Darcy-Buckingham’s equation

\[ q = -K(h) \frac{dH}{dz} \]  

(2-3)

Where \( q \) is the water flux (m/s), \( K(h) \) the unsaturated hydraulic conductivity (m/s), \( H \) the total hydraulic head, \( h \) the negative water pressure (m), and \( z \) is the elevation height (m). The relationship between \( h \) and \( z \) is shown below:

\[ H = h + z \]  

(2-4)

Although Eq. 2.1 and Eq. 2.3 have the similar format, where water flux is proportional to the hydraulic gradient, the fundamental definitions are different. In Eq. 2.1, \( K_r \) is the hydraulic conductivity corresponding to hydraulic gradient, while in Eq. 2.3, \( K(h) \) is the hydraulic conductivity corresponding to a representative volume of the porous medium.

Due to the complexity of \( K(h) \), only empirical relationships exist to estimate it. For example, Van Genuchten developed an equation to represent the unsaturated hydraulic conductivity.

\[ K(\theta) = K_s \left[ \frac{\theta - \theta_r}{\theta_s - \theta_r} \right]^{\lambda} \left[ 1 - \left( \frac{\theta - \theta_r}{\theta_s - \theta_r} \right)^{1/m} \right]^2 \]  

(2-5)

where \( K_s \) is the saturated hydraulic conductivity (m/s), \( \theta \) is volumetric soil water content (m³/m³), \( \theta_s \) is the saturated water content (m³/m³), which equals to the porosity of the soil sample, \( \theta_r \) is the water residence content (m³/m³), and the \( n, m, \lambda \) are empirical constants. Besides, there exists the relationship between the water content \( \theta \) and the negative water pressure \( h \), which is displaced below.

\[ \frac{\theta - \theta_r}{\theta_s - \theta_r} = \frac{1}{[1 + (\alpha h)^n]^{m}} \]  

(2-6)
where the parameters m, n, α (m-1) determine the shape of the water retention curve. However, it is often assumed that \( m = 1 - 1/n \), so the parameters needed to represent the relationship between hydraulic conductivity and soil water pressure are \( K_s, \theta_s, \theta_r, n, \lambda, \) and \( \alpha \).

Darcy’s equation (Eq. 2.3) which uses the conceptual model of a representative volume in the vadose zone at the Darcian scale has been validated by experiments (Darcy, 1856a) and by theory (Bear, 2013). There are two flow mechanisms under the Darcian scale, stable flow and unstable flow. The stable flow is the straightforward mechanism with the horizontal wetting front parallel to the soil surface. In this case the fluid moves downwards without breaking into fingers. The flow behavior of this type can be simulated by one-dimension computer graphics (Kass et al., 1990). Many column and lysimeter tests for infiltration under controlled conditions have been conducted to prove the universality of the stable flow (Philip, 1975). Besides, stable wetting fronts have been observed in desert areas (Wierenga et al., 1991), and a stable wetting front in a loam soil along the Rio Salado near Socorro was also observed (Hendrickx et al., 2001).

In contrast, the unstable preferential flow is the least understood flow mechanism (Hendrickx et al., 2005). The unstable flow starts with the horizontal wetting front but breaks into fingers or other preferential flow paths under certain conditions. These unstable flow contributes to the recharge flow and the transportation of contaminants to the groundwater with the velocities many times faster than that of the stable flow (Hendrickx et al., 1993). The occurrence of unstable flow in field has been generally observed (Gees et al., 1969; Mooij, 1957). The conditions triggering the unstable flow have not been fully investigated yet. However, based on the theoretical work supported by laboratory experiments, some conditions have been established: (1) infiltration of ponded water with compression of air ahead of the wetting front (Wang et al., 1998); (2) water-repellent soils (Ritsema et al., 1993); (3) continuous non-ponding infiltration (Selker et al., 1992); and (4) in layered soil profiles where permeable layers are underlain by coarse-textured soil layers (Clothier et al., 1977).

2.1.3 Areal Scale

At areal scale, preferential flow may result from surface depressions and discontinuous layers with lower or higher permeability (Hendrickx et al., 2005). In this scale, long and expensive field campaigns are required to characterize and quantify spatial variability of the vadose zone if
Darcy-Buckingham equation is applied, which is not practical. Hence, areal mass balance or soil moisture budgeting models are applied to evaluate the movement of water at such a big scale (Simmers et al., 1997). For regional groundwater recharge, water balance equation can be expressed as:

\[ q_r = P + R - ET - \Delta W \]  

(2-7)

where \( q_r \) is the groundwater recharge (m/month), \( P \) is precipitation (m/month), \( R \) is the net runoff/runoff (m/month), \( ET \) is actual evapotranspiration (m/month), and \( \Delta W \) is the change in soil moisture storage in the vadose zone (m/month).

2.1.4 Comparison of the Scales

The schematic of different preferential flows are shown in Figure 2-1 and Figure 2-2. The scales, conceptual models, critical parameters, and measurements relevant to flow mechanisms in the porous media are concluded and compared in Table 2-1.

Figure 2-1 Schematic showing different preferential flow mechanisms observed at pore and Darcian scales (Hendrickx et al., 2001)
Figure 2-2 Schematic showing different preferential flow mechanisms observed at the areal scale (Hendrickx et al., 2001)

Table 2-1 Scales, Conceptual Models, Critical Parameters, and Measurements Relevant to Flow Mechanisms in the Vadose (Hendrickx et al., 2005)

<table>
<thead>
<tr>
<th>Spatial Scale</th>
<th>Domain</th>
<th>Conceptual Model</th>
<th>Physical Model</th>
<th>Critical Parameters</th>
<th>Small Temporal Measurements</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pore</td>
<td>Macropores, Fractures</td>
<td>Fluid Continuum</td>
<td>Hagen-Poiseuille</td>
<td>Fracture Width</td>
<td>Thin Sections, NMR</td>
<td>Minutes, Days</td>
</tr>
<tr>
<td>Darcian</td>
<td>Laboratory, Soil Profiles</td>
<td>Representative Volume</td>
<td>Darcy-Buckingham</td>
<td>Hydraulic Properties</td>
<td>TDR, Neutron Attenuation, Tensiometers</td>
<td>Hours, Months</td>
</tr>
<tr>
<td>Areal</td>
<td>Field, Local Depression, Landscape Element</td>
<td>Mass Balance</td>
<td>Mass Balance</td>
<td>Weather, Soil Moisture</td>
<td>Meteorological Station, TDR, Neutron Attenuation, Remote Sensing, Groundwater Level</td>
<td>Days, Years</td>
</tr>
</tbody>
</table>

2.2 Correlative Parameters about Fluid Flow

To describe the movement of homogeneous fluid in vertical direction, Henry Darcy set up an experiment to investigate the relationship between water flow and other parameters. It was concluded that: flow rate $Q (\text{m}^3/\text{s})$ is proportional to the constant cross-sectional area $A$, and the difference of height at the input and the output point, and inversely proportional to the length of the porous media (Darcy, 1856b). Figure 2-3 shows the experimental set up of the Darcy’s experiment. Darcy’s Law is expressed in Eq. 2.8.
where \( Q \) is the volumetric flow rate \((\text{m}^3/\text{s})\), \( K \) is the hydraulic conductivity \((\text{m}/\text{s})\), \( A \) is the cross sectional area \((\text{m}^2)\), \( h_1 \) and \( h_2 \) are the piezometric head \((\text{m})\), and \( L \) is the length of the porous media \((\text{m})\).

\[
Q = KA(h_1 - h_2)/L
\]  
\((2-8)\)

Figure 2-3 Darcy’s Experiment Set up (Bear, 2013)

Hydraulic conductivity \( K \) is a critical factor for describing water movement through porous media, such as soil. However, laborious measurements are required to obtain hydraulic conductivity information (Bear, 2013). Attempts have been made by soil physicists to generate the property from more easily determinable soil properties (Vereecken et al., 1990). Only empirical expressions based on the experimental data are accepted to estimate hydraulic conductivities (Vereecken et al., 1990). Wind derived the relationship in the form of an exponential equation in 1955 (Wind, 1955):

\[
K(h) = a/h^n
\]  
\((2-9)\)
where $K$ is the hydraulic conductivity (cm/d), $h$ is the pressure head (cm), $a$ and $n$ are parameters that are dependent on the soil properties (Wind, 1955). In 1964, Brooks and Corey derived the equations

$$K = K_{sat}, \quad h > h_b$$

(2-10)

$$K(h) = K_{sat} \left(\frac{h}{h_b}\right)^{-(2+3\lambda)}$$

(2-11)

where $K_{sat}$ is the saturated hydraulic conductivity (cm/d); $h_b$ is the bubbling pressure on air entry value (cm); $\lambda$ is the dimensionless pore size distribution index. In 1953, Burdine considered a tortuosity factor related to the pressure term, and based on this consideration, the hydraulic conductivity can be estimated as

$$K = K_{sat} S_e^{(2+3\lambda)}, \quad h > h_b$$

(2-12)

$$S_e = (\theta - \theta_r) / (\theta_s - \theta_r)$$

(2-13)

where $S_e$ is the effective saturation (%), $\theta$ is the actual soil water content (cm$^3$), $\theta_r$ is the residual soil water content (cm$^3$), which is defined as the water content for which the gradient $d\theta/dh$ becomes zero, and $\theta_s$ is the saturated soil water content (cm$^3$), which is equal to the open pore volume of the soil matrix. Later in 1980, $S_e$ was defined as the normalized water content by Van Genuchten (Van Genuchten, 1980). Under the assumption that the residual soil water content is zero, the equation below was obtained with another empirical parameter $b$.

$$K = K_{sat} (\theta / \theta_s)^{(2b+3)}$$

(2-14)

Hydraulic conductivity is a measurement of the ease that fluid passes a porous matrix or fractures. Both the fluid properties and the matrix properties as well as the degree of saturation are the parameters influencing hydraulic conductivity. Fluid properties are the fluid density, $\rho$, and fluid viscosity, $\mu$, or in the combined form of kinematic viscosity (Bear et al., 1993). The
relevant properties of the porous media are mainly the grain size distribution, the pore size
distribution, the shape of the grains and the pores, tortuosity, the specific surface area, and the
porosity. Based on the dimensional analysis, saturated hydraulic conductivity can be expressed
as the equation below (Bear, 2013):

\[ K_{sat} = \frac{ky}{\mu} = kg/v \]  \hspace{1cm} (2-15)

where k is the intrinsic permeability of the porous matrix (cm²).

2.3 Permeability and the Approximation

Permeability is a measurement of the ability of the porous media to allow the fluid to pass
through it, which depends solely on the intrinsic characteristics of the porous media. A great deal
of work has been done to estimate the permeability based on the known parameters of the porous
media. Grain size distribution has long been recognized as an important factor that influences
permeability (Vuković et al., 1992). Eq. 2.16 is a general empirical formula that estimates
permeability based on grain size (Vuković et al., 1992).

\[ k = C \cdot f(n) \cdot d_e^2 \]  \hspace{1cm} (2-16)

where k is the permeability (cm²), C is the sorting coefficient; f(n) is the porosity function, and d_e
is the effective grain size (cm). C, f(n) and d_e are different depending on the methods used to
analyze the grain size. Different C, f(n), and d_e have been generated from previous studies.

A century ago, Hazen formula was developed to estimate the permeability of uniformly graded
sand,

\[ k = C_H d_{10}^2 \]  \hspace{1cm} (2-17)

where \( C_H \) is the Hazen empirical coefficient; and \( d_{10} \) is the particle size for which 10% of the
grains are finer (cm) (Hazen, 1911). The value of \( C_H \) is assumed to be equal to 100, and other
values between 1 and 1000 were also published in some textbooks (Lambe et al., 1969; Mansur
et al., 1962; Taylor, 1948). Although almost all geotechnical textbooks cite Hazen formula, it is inaccurate. Mansur and Kaufman found a rough correlation between \( d_{10} \) and \( k \) when he plotted \( \log(d_{10}) \) verses \( \log k \) (Mansur et al., 1962). It showed that \( C_H \) was not a constant. Besides, the relationship between \( k \) and \( d_{10}^2 \) was not linear. Specifically, when \( d_{10} = 0.1 \) cm, \( k \) is proportional to \( d_{10}^{0.7} \) (Mansur et al., 1962). \( C_H \) also varies with temperature (Hazen, 1911).

Kozeny-Carman equation was originally developed by Kozeny and was modified by Carman (Carman, 1997; Kozeny, 1927). It is a semi-empirical and semi-theoretical formula.

\[
k = \left( \frac{\gamma}{\mu} \right) \left( \frac{1}{C_{K-C}} \right) \left( \frac{1}{S_0^{2}} \right) \left( \frac{e^3}{1 + e} \right)
\]

(2-18)

where \( \gamma \) is the unit weight of permeant; \( \mu \) is the viscosity of permeant; \( C_{K-C} \) is the Kozeny-Carman empirical coefficient; \( S_0 \) is the specific surface area per unit volume of particles (1/cm); and \( e \) is the void ratio, which can be calculated by porosity (Santamarina et al., 2001). \( C_{K-C} \) was reported to be 4.8 ± 0.3 for uniform spheres, and was always assumed to be 5 (Carman, 1997). For a given temperature, \( \gamma \) and \( \mu \) are known properties, but \( S_0 \) cannot be simply estimated by particle size distribution when the shape of the particles are heterogeneous. If the porous media is composed of uniform spheres in diameter \( D \) (cm),

\[
S_0 = \frac{\text{area}}{\text{volume}} = \frac{\pi D^2}{(\pi D^3/6)}
\]

(2-19)

At 20\(^{\circ}\), \( \gamma/\mu \) for water is \( 9.93 \times 10^4 \) 1/cm s. Substitute these parameters into equation 2.18 to obtain Eq. 2.20

\[
k = 552D^2 \left( \frac{e^3}{1 + e} \right)
\]

(2-20)

If the particles comprising the porous media are not uniform, the particle size distribution is represented by the effective diameter \( D_{\text{eff}} \).
\[ D_{\text{eff}} = \frac{100\%}{\left[ \sum \left( \frac{f_i}{D_{\text{ave}i}} \right) \right]} \quad (2-21) \]

where \( f_i \) is the fraction of particles between two sieve sizes, and \( D_{\text{ave}i} \) is the average particle size between two sieve sizes (cm). So

\[ S_0 = \frac{6}{D_{\text{eff}}} \quad (2-22) \]

Besides, the shape difference of the individual particles influences \( S_0 \), so there should be a shape factor \( SF \) in the expression of \( S_0 \). Thus,

\[ S_0 = \frac{SF}{D_{\text{eff}}} \quad (2-23) \]

The value of \( SF \) has been suggested by previous literatures: spherical – 6.0; rounded – 6.1; worn – 6.4; sharp – 7.4; angular – 7.7 (Amos et al., 2009; Fair et al., 1933). There is also another set of values assigned by Loudon: rounded – 6.6; medium angularity – 7.5; and angular – 8.4 (Loudon, 1952). Combining terms and substituting the values of the known constants, Eq. 2.20 is converted to

\[ k = 1.99 \times 10^4 \left( \frac{100\%}{\sum \left( \frac{f_i}{D_{\text{ave}i}} \right)} \right)^2 \left( \frac{1}{SF^2} \right) \times \left( \frac{e^3}{1 + e} \right) \quad (2-24) \]

The generation of Kozeny-Carman formula improves the accuracy of Hazen formula, but Hazen formula has continued to be used because of its simplicity (Carrier III, 2003). Some limitations constrain the use of Kozeny-Carman Formula. For example, clayed soils with electrochemical reactions between the soil particles do not satisfy the conditions to apply the formula. Additionally, Kozeny-Carman formula cannot be applied to coarse samples without Darcian conditions.

In 1998, Kresic derived Breyer formula to estimate permeability for materials with heterogeneous size distributions and poorly sorted grains (Eq. 2.25).
\[ k = 6 \times 10^{-4} \times \log\left(\frac{500}{C_u}\right) \times d_{10}^2 \]  \hspace{1cm} (2-25)

where \( C_u \) is the uniformity index, which is calculated from

\[ C_u = \frac{d_{60}}{d_{10}} \]  \hspace{1cm} (2-26)

where \( d_{60} \) and \( d_{10} \) represent grain size in diameter (cm), for which 60\% and 10\% of the sample respectively, are finer than (Anderson, 1997). This method does not include the effect of porosity, and is mostly useful for the samples with \( C_u \) between 1 and 20, and with grain size between 0.06 mm to 0.6 mm (Odong, 2007).

Considering the effect of porosity, Slitcher generated a formula that includes both \( d_{10} \) and porosity, \( n \) (Slitcher, 1899).

\[ k = 1 \times 10^{-2} \times n^{3.287} d_{10}^2 \]  \hspace{1cm} (2-27)

The porosity, \( n \), may be derived from the uniformity index based on an empirical relationship (Vuković et al., 1992),

\[ n = 0.255(1 + 0.83C_u) \]  \hspace{1cm} (2-28)

This formula is most applicable for grain size between 0.1 mm to 5 mm (Odong, 2007).

For large grain sands, Terzaghi formula is appropriate (Cheng et al., 2007).

\[ k = C_t \left(\frac{n - 0.13}{\sqrt{1 - n}}\right)^2 d_{10}^2 \]  \hspace{1cm} (2-29)

where \( C_t \) is the sorting coefficient between \( 6.1 \times 10^{-3} \) and \( 10.7 \times 10^{-3} \), and the average value of \( C_t \), \( 8.4 \times 10^{-3} \), has been used in some studies (Odong, 2007).
For medium grain size samples with uniformity coefficient less than 5, U.S. Bureau of
Reclamation (USBR) formula is used to estimate the permeability, where the effective grain size
is $d_{20}$, and the porosity function is unity, which means it is independent of the porosity (Cheng et
al., 2007).

\[ k = 4.8 \times 10^{-4} d_{20}^{0.3} d_{20}^{-2} \]  \hspace{1cm} (2-30)

Moreover, there is an empirical formula, Alyamani & Sen, to estimate the permeability. It does
not follow the general relationship stated above, but it is also a grain-size-dependent equation for
permeability analysis. It includes both $d_{10}$ and $d_{50}$, as well as the sorting characteristics.

\[ k = 1.5046 \times (I_0 + 0.025 \times (d_{50} - d_{10}))^2 \]  \hspace{1cm} (2-31)

where $I_0$ is the intercept (mm) of the line formed by $d_{50}$ and $d_{10}$ with the grain-size axis, $d_{10}$ is
the particle size for which 10% of the grains are finer (mm), and $d_{50}$ is the particle size for which
50% of the grains are finer (mm).

Several studies have been conducted to compare and evaluate the accuracy of these empirical
relationships listed above (Eq. 2.17, Eq. 2.18, Eq. 2.20, Eq. 2.24, Eq. 2.25, Eq. 2.27, Eq. 2.29, Eq.
2.30 and Eq. 2.31) based on the grain size (Cheng et al., 2007; Odong, 2007; Sezer et al., 2009).
The results of the studies indicate that different equations are appropriate for samples with
different grading characteristics. These methods are capable but not sufficient for the accurate
prediction of permeability in terms of the narrow grain size range in which these methods are
applicable (Sezer et al., 2009). For a wide range of soil types, Kozeny-Carman’s formula
followed by Hazen formula is found to be the best overall estimation method (Odong, 2007).
However, for highly heterogeneous soil samples, Breyer formula results in a better estimation of
the permeability (Odong, 2007).

2.4 Measurement of Particle Size Distribution

Estimating permeability by grain-size distribution has been regarded as a less expensive than
field tests, and it is independent of geometry and hydraulic boundaries of the aquifer compared
with laboratory tests (Uma et al., 1989). Hence, in the approximation of permeability, the
relatively easy-to-measure grain size distribution is the critical information to the description of the porous media (Cirpka, 2003). Except for spheres and cubes, whose size can be described by the single linear dimension, the size for a particle, typically of an irregular shape, depends on the length measured and the measurement method (Bear, 2013). Two methods are introduced in the following sections, which are sieve analysis and image analysis method.

2.4.1 Sieve Analysis

Sieve analysis is to shake the tested material on a sieve with square openings of specific size, so that the “size” of a particle is determined by the side length of the square hole in the screen (Bear, 2013). However, the probability for the particle to pass is influenced by the shape of the particle and the shape of the sieve opening. For example, that a particle can only pass the opening in one orientation limits the chance to pass the sieve. Hence, to achieve the largest passing rate, long time shaking is required. In fact, it is almost impossible to achieve the complete sorting of a given size range (Gee et al., 2002). The typical size for sieve analysis is between 50 µm and 2000 µm (Gee et al., 2002).

The total mass of the material retained on the sieve is affected by the load and the particle shape, and it is also a function of time (Grozubinsky et al., 1998).

\[
\frac{d}{dt} M_t = -k(M_t - M_r)
\]

(2-32)

where \( M_t \) is the total mass of material on the sieve at time \( t \); \( M_r \) is the mass of the material that cannot pass the sieve; and \( k \) is the passing rate factor which was found to be time-dependent, where \( k=ct^m \) (Grozubinsky et al., 1998). After integration, Eq. 2.32 can be rewritten as

\[
M = M_0(1 - e^{-ct^n})
\]

(2-33)

where \( M_0 \) is the particle mass that would pass the sieve after infinite sieving time; \( M \) is the cumulative mass of material that has passed the sieve at time \( t \); and \( n=1-m \) (Gee et al., 2002). Experiments have been done to generate the values of \( c \) and \( n \). It was found that increasing the fraction of oversized particles reduced the values of both parameters. Besides, the larger the
samples, the smaller the parameters are (Allen, 2013). Hence, oversized particles decreases sieving efficiency and increases the required sieving time. Figure 2-4 shows the effect of sieving time and load on the amount of samples passing the same size sieves. The time-dependent passing efficiency results in an apparent coarsening of the particles compared to the true size (Gee et al., 2002).

![Sieving curves for (A) glass beads and (B) sands in a 50-mesh square wire sieve. Both of the samples have the same nominal mass of 110 g (Aslan et al., 1998)](image)

2.4.2 Image Analysis

Particle size distribution can also be obtained by imaging technique followed by digital image processing. Image-based methods offer the potential to extract both the quantitative and qualitative information of the particle size distribution (Sarkar et al., 2009). This method depends on the advances of the digital image processing technique that allows the particle size related data to be extracted from the images (Vernon, 1991).

However, there are several aspects that should be taken into consideration. First, to represent the whole particle population, images need to be captured in multiple layers at different angles. Second, to increase the reliability of the results, the information extracted from the images should be as much as possible based on the statistical nature of this method, which can be achieved by analyzing a large number of images taken under the same conditions (Al-Thyabat et al., 2006). Third, using a single parameter, or single mathematical model to estimate the particle size distribution may not be necessarily accurate without the particle shape information (Al-
Thyabat et al., 2006). Combining the shape and the size information of the particles may improve the results. For example, Orive (1978) measured the probability density function (PDF) of the size of spheroids from the size–shape (PDF) of ellipses. Ohse and Nippe (1997) estimated the size density function of cubic particles by using the size–shape density function of polygons (Ohser et al., 1997). Finally, the results derived from the image analysis technique, in some cases, can be compared with those derived from the sieve analysis to validate the accuracy of this method.

2.5 Measurement of Porosity

2.5.1 Definition of Porosity

Description of individual pores formed in packed solid grains is impossible. Practically, only statistical representative parameters are used to describe pore structure in porous media. (Bear, 2013). Porosity, a property of the macroscopic porous media, is defined as the ratio of the volume of the void space ($U_v$) to the bulk volume ($U_b$) as Eq. 2.34 (Bear, 2013).

$$n = \frac{U_v}{U_b} = \frac{U_b - U_s}{U_b}$$

where $U_s$ is the volume of solids within $U_b$. Porosity, a dimensionless quantity, is typically expressed as percentages. When $U_v$ in Eq. represents the total void space in the porous media, the porosity calculated corresponds to the absolute or total porosity. However, only interconnected pores facilitate fluid flow through porous media. Hence, the concept of effective porosity, $n_e$, is defined as the ratio of the interconnected pore volume to the bulk volume as Eq. 2.35 (Bear, 2013).

$$n_e = \frac{(U_v)_e}{U_b}$$

and
\[(U_v)_e + (U_v)_{ne} = U_v\]  \hspace{1cm} (2-36)

where \((U_v)_e\) is the effective pore volume, and \((U_v)_{ne}\) is the non-effective pore volume.

Non-interconnected pores do not contribute to fluid flow. Two types of interconnected pores also contribute little to fluid flow, the dead-end pores and the stagnant pockets. The two types of pores, shown in Figure 2-5, form pockets that cause fluid to be stagnant.

The porosity of consolidated materials is mainly determined by the degree of cementation, while the porosity of unconsolidated materials is determined by the packing methods, the grain shape, arrangement and size distribution (Bear, 2013). Finer particles have a more significant effect on porosity than coarse particles (Salisbury et al., 1985). For spherical particles of uniform sizes, the porosity is 47.6\% by cubical packing, and 26.0\% by rhombohedral packing which is the most compact packing method (Bear, 2013). The porosity falls between these two values for other packing methods. However, for porous media consisting of particles of non-uniform sizes, the porosity cannot be calculated directly. Some typical porosity values of natural sedimentary materials are shown in Table 2-2.

Figure 2-5 Dead-end pores (Bear, 2013)

<table>
<thead>
<tr>
<th>Sedimentary Materials</th>
<th>Porosity (%)</th>
<th>Sedimentary Materials</th>
<th>Porosity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>peat soil</td>
<td>60-80</td>
<td>fine-to-medium mixed sand</td>
<td>30-35</td>
</tr>
<tr>
<td>soils</td>
<td>50-60</td>
<td>gravel</td>
<td>30-40</td>
</tr>
<tr>
<td>clay</td>
<td>45-55</td>
<td>gravel and sand</td>
<td>30-35</td>
</tr>
<tr>
<td>silt</td>
<td>40-50</td>
<td>sandstone</td>
<td>10-20</td>
</tr>
<tr>
<td>medium-to-coarse mixed sand</td>
<td>35-40</td>
<td>shale</td>
<td>1-10</td>
</tr>
<tr>
<td>uniform sand</td>
<td>30-40</td>
<td>limestone</td>
<td>1-10</td>
</tr>
</tbody>
</table>
2.5.2 Measurement of Porosity

There are two main types of methods to measure porosity, direct and indirect methods (Bear, 2013). The methods based on the volume determination such as U_s, U_b and U_v are direct methods. Other methods which are based on the property of pores are called indirect methods. Some examples are given here. Mercury injection method is based on the measurement of U_b and U_v. Mercury is a non-wetting liquid when in contact with most solids (Mayka et al., 2013). The sample is placed into a chamber with mercury of known volume under the atmosphere pressure. The volume of mercury displaced by the sample is U_b. With the increase in the applied pressure on the mercury, it flows into the pores of the sample. The total void space U_v can be determined (Hemes et al., 2013).

Bulk density method to measure porosity is based on the difference between the dry bulk density and the solid density (Weil et al., 2016). It is conducted by measuring the mass of dry solids packed in a container of a given volume so that the bulk density can be calculated (Avnimelech et al., 2001). The given volume contains solid volume and void space volume. The porosity is calculated by

\[
 n = \left[ 1 - \left( \frac{\text{bulk density}}{\text{solid density}} \right) \right] \times 100\% \tag{2-37}
\]

Method of liquid absorption to measure the effective porosity is a quick, economical and reliable method (Maria, 2010). After drying and removal of air, the pores are filled with a liquid medium of known density, and the effective porosity can be calculated from the mass change (Maria, 2010). The assumption of this method is that during the procedure, the weight of the samples does not change, and solid parts cannot be penetrated by the liquid (Maria, 2010).

Gas expansion technique is based on the principle that two materials tend to contact each other when one is in gaseous and the other is in solid state. It is also based on the Boyle-Mariotte’s gas law. The experimental setup is shown in Figure 2-6. The sample is placed in a chamber of volume U_1 and initial pressure P_1. The valve between U_1 and U_2 is then open to allow the expansion of the gas into U_2, where the initial pressure is P_0. After the expansion, the final
pressure in the connected chamber is $P_2$. Hence, an equation is generated based on the Boyle-Mariotte’s gas law (Bear, 2013).

$$p_1(U_1 - U_s) + p_0 U_2 = p_2(U_1 + U_2 - U_s)$$

(2-38)

Based on the Eq. 2.38, the solid volume $U_s$ is calculated. Comparing $U_s$ with $U_1$, the porosity is derived.

![Figure 2-6 Experimental setup based on the Boyle-Mariotte’s gas law (Bear, 2013)](image)

Microscopy can be used to visualize the structure of pores formed in porous media, which gives information on porosity and pore locations (Maria, 2010). In this measurement, a wide range of pore sizes can be detected, and therefore a pore size distribution can be derived. Pores and cracks within the porous media can be distinguished. The disadvantage of this method is the practical limit of the magnification capacity (Scrivener, 1997).

2.6 Summary

The motivation of this research is to study the behavior of fluid flow in the unsaturated porous media, i.e., dump leach pads. The permeability of the porous media is closely related with the pore size distribution and particle size distribution. Thus, this research aims at advancing the understanding of the particle size distribution and pore size distribution in the highly heterogeneous dump leach pads.
Chapter 3. Particle Size Analysis Using Aerial Image Processing

3.1 Introduction

This chapter gives a detailed description of the analysis of particle size distribution. The research background has been introduced in Chapter 2; the research procedures and methodology are presented in Section 3.2; the results and discussion are demonstrated in Section 3.3; and the conclusions are showed in Section 3.4. The content of this chapter has been published in Hydrometallurgy (Zhang et al., 2017).

3.2 Methodology

3.2.1 Image Acquisition

The case study site was the Quebrada Blanca (QB) copper mine located in northern Chile. The operation produces copper cathodes using heap and dump leaching, solvent extraction, and electrowinning. This study aimed at investigating the particle size distribution of the dump leach pad, which was constructed via end dumping of the run-of-mine ore using haulage trucks without further crushing of the ore. During dump construction, a new dump face was formed after a truck load of ore was deposited over the previous dump face. Images of various dump faces were taken using a camera installed on a drone operated by San Lorenzo S.A. (Iquique, Chile). The angle of repose was between 30° and 40°. The camera was adjusted roughly in parallel with the dump faces at an angle of 35°. Four PVC pipes of 1-m length and 1-inch diameter painted in orange that provided high visibility were placed on the leach pad in the shape of a square as the reference size for the subsequent image calibration. Figure 3-1 (left) shows a schematic of the dump construction via end dumping and the setup for the image acquisition. Figure 3-1 (right) shows an actual photo of the drone in the process of acquiring images at the case study mine. The image resolution achieved was 4000 × 3000 pixels.
Figure 3-1 Schematic for dump construction via truck end dumping and the setup for the image acquisition (left); a drone in the process of acquiring images of the leach pad at the case study mine (right)

3.2.2 Image Processing

Ten images in total, each representing a distinct dump face, were selected for the image analysis using ImageJ software, an open source platform designed for scientific image analysis (https://imagej.net). The image analysis procedure has been explained elsewhere (Zhang et al., 2016). The original RGB color images were imported to the software and converted to 8-bit grayscale images. The image calibration provided a pixel-to-real-distance conversion factor of 1.734 cm, i.e., each pixel was converted to a real world distance of 1.734 cm. Therefore, the height of the dump from the top to the toe in the images was calibrated to be 34 m and the horizontal distance from the left to the right in the images was calibrated to be 65 m. The software assigned each pixel a single number that represented the brightness of the pixel, the so called “pixel intensity value”. The range of pixel intensity values in a grayscale image is between 0 and 255, with zero being black, 255 being white, and the values in between making up different shades of gray. Ore grain sizes can be obtained from image analysis on the basis that the boundaries of rock particles are generally darker than the interior, meaning that there are sharp changes in the intensity value from boundaries to the interior (Chi, 2011). After the image calibration, the boundaries of the ore particles were detected and emphasized by applying “Find Edges”. This was done through a Sobel filter, an image processing algorithm for edge detection in images by using two $3 \times 3$ convolution kernels to calculate vertical and horizontal derivatives.
of the image intensity function. Image thresholding was then applied to convert the image to a binary image, i.e., partition the image into ore particles (foreground) and background. Finally, the surface area of each ore grain was analyzed and the results were exported to a Microsoft Excel spreadsheet, where the surface area was converted to the equivalent sphere diameter. The cumulative volume of all spherical particles in one image was estimated to be about 467 m$^3$, which gave a total volume of 4,670 m$^3$ of ore from the ten images studied by the image analysis technique.

3.2.3 Statistical Interpretation of Results

Even though efforts were made to obtain a perfect view of the entire dump face, imperfections were still found in six of the ten images due to the large dimension of the leach pad. The imperfections were on the part of the images that represented the top 2 m and the toe of the dump. Among the ten images selected for the study, four images with a satisfactory view from the very top to the toe of the dump were chosen for the analysis of the particle size distribution of the entire dump. Each chosen image was processed individually to extract data of the particle size distribution of the dump face formed. The data from the individual images were then combined to derive the average particle size distribution for the entire dump.

To study the segregation of fine and coarse particles along the dump face, each of the ten images was segmented into sub images that represented different depths along the dump face. The segmentation started with the first sub image representing the top 2 m and continued with every 4 m until the toe of the dump. Ideally, there should be ten sub images for each depth. However, due to the image imperfections on the top and at the toe, there were eight sub images representing the top 2 m, ten sub images representing the intermediate zone from the depth of 2 m to 26 m, six sub images representing the depth from 26 m to 30 m, and five sub images representing the last 4 m from the depth of 30 m to 34 m. All sub images were processed individually to extract data of the particle size distribution. Then data from all sub images that represented a particular depth were combined to derive the average particle size distribution for that depth. The standard deviation from all the sub images for a particular depth was calculated and presented as error bars in the Figure 3-6(A).
3.2.4 Possible Inaccuracy Caused by Image Quality

The accuracy of the image analysis results was subjected to the quality of the images, which could be compromised by such issues as shadows and blurry particle boundaries caused by uneven natural lighting. One possible consequence was that the percentage of fine particles was underestimated. This could occur when a cluster of fine grains was wrongly identified as one single large particle because of no significant changes in the pixel intensity values among the fine particles in the cluster. To minimize this effect, manual adjustment that involved manually circling out the largest particles in individual images was applied. In this way, the largest possible diameter was known. Any particles larger than this diameter were considered as fine particle clusters instead of one large particle. These presumed fine particle clusters were then converted to certain numbers of fine particles under two assumptions: (1) the diameter of the fine particles was equivalent to the smallest identifiable particle size in a particular image, typically between 1 and 2 cm; and (2) the surface area of the cluster was equivalent to the sum of the surface area of all fine particles. Another consequence was that the percentage of extremely large particles was underestimated. Large particles tended to be more susceptible to shadows caused by uneven natural lighting. These shadows could cause abrupt changes in pixel intensity values in a large particle, resulting in the large particle being mistakenly segmented into multiple smaller particles during the image processing. No special care was taken to minimize this effect.

3.3 Results and Discussion

3.3.1 Average Particle Size Distribution in the Dump Leach Pad

Figure 3-2 (left) shows an example of a calibrated image of a dump face formed and Figure 3-2 (right) shows the corresponding binary image created after the image thresholding. A wide range of grain sizes could be visually observed in the image. Figure 3-3 shows the particle size distributions derived from the four satisfactory images chosen that represented four distinct dump faces formed during the dump construction. The results exhibited little variation or spread across different dump faces and provided consistent evidence that the dump leach pad was made up of particles of a wide range of sizes. The smallest particles that could be identified in the images, which were dictated by the image resolution, were between 1 cm and 2 cm in diameter. The largest particles identified in the images were larger than 200 cm in diameter. P_{80}, i.e., the
particle size for which 80% of particles by volume are finer, was 200 cm. This value was significantly higher than the value derived from the sieve analysis and historically used by the mine operation (10 to 25 cm) in their estimation of metal extraction.

Figure 3-2 An example of a calibrated image of a dump face (left); the corresponding binary image after edge detection and image thresholding (right)

Figure 3-3 Particle size distribution derived from the four images representing the four distinct dump faces

The stark difference of $P_{80}$ obtained from the sieve analysis and the image analysis was attributed to the measurement range of sieve analysis, which was limited by available sieve sizes. Particles larger than certain sizes could not be measured and were not included in the analysis, leading to
the result that was unrepresentative of the particle size distribution of the whole dump. However, sieve analysis may provide a valuable estimation of the particle size distribution in the fine particle range, in which image analysis is incapable of analyzing due to the constraint posed by the image resolution. Figure 3-4 (A) shows that the particle size distribution derived from the sieve analysis covered the range from 0.01 cm to 20 cm. This included the range in which the image resolution was not sufficiently high for the analysis of the fine particle sizes. Together, they provided a full spectrum of the particle size distribution in the dump leach pad, which is shown in Figure 3-4 (B).

Figure 3-4 Particle size distribution from the sieve analysis in the fine particle range from 0.01 cm to 20 cm (A); Combination of particle size distribution derived from the sieve analysis and the image analysis (B)

3.3.2 Spatial Segregation of Fine and Coarse Particles

Figure 3-5 shows the particle size distributions at different depths of different dump faces. The results were derived by segmenting the individual images into multiple sub images representing different depths of different dump faces. For a particular depth, the particle size distributions of different dump faces at the same depth were different and the spreading of these lines suggested the existence of lateral heterogeneity. The spreading was particularly apparent in the intermediate zone at the depths of 10 m and 14 m, indicating a more pronounced lateral segregation in this zone.
Discernable differences in the spread of these lines across different particle size ranges were observed. For all depths, the lines exhibited more pronounced spreading within the large particle range than within the fine particle range, which was manifested by the different magnitudes of variation of the characteristic diameters, $d_{10}$, $d_{50}$, and $d_{80}$, i.e., grain sizes for which 10%, 50% and 80% of the grains fall below by volume (Figure 3-6 (A)). At any depth, the variation of $d_{10}$ was much smaller than those of $d_{50}$ and $d_{80}$. Furthermore, with increasing depth there was an increase in $d_{10}$, $d_{50}$ and $d_{80}$. The value of $d_{10}$ exhibited a consistent increase with depth, whereas $d_{50}$ and $d_{80}$ showed some fluctuations in the intermediate zone. This suggested that fine particles tended to be concentrated on the top and coarse particles moved further downwards along the dump face, suggesting a vertical segregation of the fine and coarse particles. The spatial heterogeneity, both laterally and vertically, would increase the likelihood of the occurrence of preferential flow.

Figure 3-5 Particle size distribution along different dump faces at different depths from the top to the toe. Different lines represent different dump faces being analyzed
These results raised an interesting question on what would be a more effective characteristic diameter to use in dump leaching. Traditionally, mine operations use d$_{80}$ (or P$_{80}$) to denote particle size distribution in concentrators and maybe in leaching operations. However, in dump leaching, d$_{50}$ and d$_{80}$ were susceptible to the occurrence of extremely large particles and thus exhibited a high degree of uncertainty and variability. The presence of those large particles explained the particle size distribution curves not being smooth in the coarse particle range. Therefore, the use of d$_{80}$ as the basis for estimating metal recovery in dump leaching was deemed questionable. Instead, d$_{10}$, given its consistency, was recommended as a more effective value to use in this context. In fact, d$_{10}$ was defined as the effective grain size and was used as the parameter for the estimation of soil permeability in the Hazen formula (Chapuis, 2012).

![Characteristic diameters: d$_{10}$, d$_{50}$ and d$_{80}$](image)

![Uniformity coefficient and coefficient of gradation](image)

Figure 3-6 Characteristic diameters: d$_{10}$, d$_{50}$ and d$_{80}$, with the error bars representing the standard deviations from all sub images for a particular depth (left); Uniformity coefficient and coefficient of gradation, along the dump face from the top to the toe (right)

In reference to the analysis of the gradation of soils, the gradation of ore particles in the dump leach pad was examined. Some commonly used measures of gradation in soil mechanics are the uniformity coefficient defined as the ratio of d$_{60}$ to d$_{10}$, and the coefficient of gradation defined as the square of d$_{30}$ divided by the product of d$_{60}$ and d$_{10}$. The higher the values, the larger the range of the particle sizes in the soil. For the soil to be well graded, i.e., the soil mass contains particles of a wide range of sizes, the value of the uniformity coefficient has to be greater than 4 and the
The coefficient of gradation should be in the range of 1 to 3. Figure 3-6 (B) shows the uniformity coefficient and the coefficient of gradation at different depths of the dump leach pad.

The top 2 m had the highest uniformity coefficient and the coefficient of gradation, suggesting that the particles on the top 2 m were remarkably well graded. There was a sudden drop followed by a slight decrease in these two parameters as the depth increased, suggesting that the gradation of the particles was decreasing. Despite this decrease, the uniformity coefficient values were all above 4. This indicated that the ore particles were still well graded towards the toe of the dump.

3.3.3 Effect of Particle Size Distribution on Ore Surface Area and Dump Permeability

The spatial heterogeneity in the particle size distribution has important implications for the leaching process. As the depth increased, the Sauter mean diameter, $d_{32}$, which reflects the ratio of the total volume to the total surface area, increased as shown in Figure 3-7 (left), indicating that the total surface area available for the leaching reactions decreased. This was in agreement with the increase in $d_{10}$ with depth. These results only shed light on the particle size distribution prior to leaching. As leaching proceeds, physical and chemical factors could cause the breakdown of coarse particles into smaller ones, resulting in continuous changes in the particle size distribution in leach pads (Ghorbani et al., 2013; Rucker, 2015).

The permeability of the dump $k$ (in cm$^2$) was estimated based on the effective particle size, $d_{10}$ (in microns), by a formula similar to the Hazen formula: $k = 0.617 \times 10^{-11} \times d_{10}^2$ (Bear et al., 1993). It is understood that certain conditions must be met to apply the Hazen formula (Chapuis, 2012). The intention here was to demonstrate the trend of the permeability change in response to the particle size change, not to derive absolute values of the permeability, which could be a rather complex formula. Figure 3-7 (right) shows that the permeability of the leach pad was extremely high and was increasing with increasing depth. This indicated that the dump was prone to the development of preferential flow via various pathways, such as rapid flow through macropores formed by coarse particles, fluid bypassing of fine particle layers of poor permeability, and fingering and unstable flow generated from stacking a fine layer of ore atop a coarse layer (Rucker et al., 2017).
3.4 Conclusion

The particle size distribution of the dump leach pad at the case study mine was characterized by analyzing the aerial images acquired by a camera installed on a drone. The image analysis results showed that particles in the dump covered a wide range of sizes from less than 2 cm to larger than 200 cm in diameter. Furthermore, a spatial heterogeneity in the particle size distribution from the top to the toe of the dump was observed. This was attributed to the segregation of fine and coarse particles during the dump construction via end dumping, i.e., finer particles tended to be concentrated on the top of the dump and larger particles moved downward along the dump face. The characteristic particle size $d_{80}$ (or $P_{80}$), traditionally used by mine operations, was deemed to be questionable to represent particle size distribution in dump leach pads, given its high degree of uncertainty and variability. Instead, the highly consistent $d_{10}$ was recommended as a more effective parameter to use for characterizing particle size distribution in those contexts.

The spatial particle size segregation would have important implications for the chemical leaching in the dump leach pad. The Sauter mean diameter was found to increase with increasing depth, indicating that the surface area available for the leaching reactions decreased with depth. Meanwhile, the dump permeability, which seemed to be extremely high, increased with depth, suggesting that the spatial heterogeneity may cause preferential flow to occur. The findings of this study demonstrated the importance of characterization of particle size distribution in
ore/rock piles for determination of fluid flow and the amounts of solutes leached. In addition, understanding the possible large particle effect on the leaching process may guide the modern blasting technology to control the size of the largest particles.
Chapter 4. Porosity Analysis using the Bulk Density and CT Imaging methods

4.1 Introduction

Porosity and pore size distribution are the key factors for determining the permeability of porous media. Particle size distribution is considered as a relatively simple and straightforward parameter to estimate porosity and pore size distribution. Hence, determining the relationship between pore size distribution and particle size distribution is critical for the estimation of permeability and flow properties. In this chapter, the porosities of samples of different particle size distributions were measured and their pore size distribution were qualitatively evaluated. The methods applied include the bulk density measurement and the CT imaging techniques.

4.2 Methodology

4.2.1 Experimental design

In Chapter 2, various methods were introduced for porosity measurements. Two methods were selected in this research: the bulk density and CT imaging techniques. The particle size range tested was selected based on the particle size distribution of a dump under leach, which was reported in Chapter 3. The particle size in the dump was found to range from less than 2 cm to larger than 2 m. Given the impracticality of testing particles of 2 m in diameter in laboratory, a parallel size distribution was selected where the shapes of the particle size distribution curves were similar. The size range tested in the laboratory was from 0.04525 mm to 6.83 mm in diameter.

Three particle size sorting conditions were tested, which are narrow-sized samples, poorly sorted samples, and well sorted samples. Narrow-sized particles were collected between two sieves of neighboring sizes. The sieve sizes and the corresponding particle sizes are shown in Table 4-1. Due to its narrow range, the size of the particles collected between two sieves of neighboring sizes was defined as the average of the two sieve openings. Poorly sorted samples were prepared as the mixtures of the narrow-sized particles of wide size variations. Each mixture contained two different narrow sized particles, one representing the fine particles and the other representing the
coarse particles, with different fractions in the mixture. The increasing level of size variation between the fine and coarse particles represented the increasing level of size heterogeneity. All poorly sorted samples and their fractions of fine and coarse particles are shown in Table 4-2. Moreover, three well sorted samples were tested, which were prepared as mixtures of four narrow-sized particles of neighboring sizes, each component size accounting for 25% by weight in the mixture. The sizes of the well sorted samples are shown in Table 4-3. The size of each well sorted sample was calculated as the average size of the four component fractions.

![Experiment apparatus designed for the bulk density measurement](image)

**Table 4-1 Narrow Sized Samples Size**

<table>
<thead>
<tr>
<th>Sample No.</th>
<th>Sieve No.</th>
<th>Sieve Opening Size (mm)</th>
<th>Average Particle Size in Diameter (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.5</td>
<td>0.313</td>
<td>5.66 8</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>3.5</td>
<td>4 5.66</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>5</td>
<td>2.38 4</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>8</td>
<td>2 2.38</td>
</tr>
<tr>
<td>5</td>
<td>16</td>
<td>10</td>
<td>1.19 2</td>
</tr>
<tr>
<td>6</td>
<td>18</td>
<td>16</td>
<td>1 1.19</td>
</tr>
<tr>
<td>7</td>
<td>25</td>
<td>18</td>
<td>0.707 1</td>
</tr>
<tr>
<td>8</td>
<td>35</td>
<td>25</td>
<td>0.5 0.707</td>
</tr>
<tr>
<td>9</td>
<td>45</td>
<td>35</td>
<td>0.354 0.5</td>
</tr>
<tr>
<td>10</td>
<td>60</td>
<td>45</td>
<td>0.25 0.354</td>
</tr>
<tr>
<td>11</td>
<td>80</td>
<td>60</td>
<td>0.177 0.25</td>
</tr>
<tr>
<td>12</td>
<td>120</td>
<td>80</td>
<td>0.125 0.177</td>
</tr>
<tr>
<td>13</td>
<td>170</td>
<td>120</td>
<td>0.088 0.125</td>
</tr>
<tr>
<td>14</td>
<td>230</td>
<td>170</td>
<td>0.0025 0.088</td>
</tr>
</tbody>
</table>
Table 4-2 Components of Poorly Sorted Samples

<table>
<thead>
<tr>
<th>Components No.</th>
<th>Components Size (mm)</th>
<th>Fractions (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.83</td>
<td>0  25  50  75  100</td>
</tr>
<tr>
<td></td>
<td>0.04525</td>
<td>100 75 50 25 0</td>
</tr>
<tr>
<td>2</td>
<td>4.83</td>
<td>0  25  50  75  100</td>
</tr>
<tr>
<td></td>
<td>0.1065</td>
<td>100 75 50 25 0</td>
</tr>
<tr>
<td>3</td>
<td>3.19</td>
<td>0  25  50  75  100</td>
</tr>
<tr>
<td></td>
<td>0.151</td>
<td>100 75 50 25 0</td>
</tr>
<tr>
<td>4</td>
<td>2.19</td>
<td>0  25  50  75  100</td>
</tr>
<tr>
<td></td>
<td>0.2135</td>
<td>100 75 50 25 0</td>
</tr>
<tr>
<td>5</td>
<td>1.595</td>
<td>0  25  50  75  100</td>
</tr>
<tr>
<td></td>
<td>0.302</td>
<td>100 75 50 25 0</td>
</tr>
<tr>
<td>6</td>
<td>0.8535</td>
<td>0  25  50  75  100</td>
</tr>
<tr>
<td></td>
<td>0.6035</td>
<td>100 75 50 25 0</td>
</tr>
</tbody>
</table>

Table 4-3 Components of Well Sorted Samples

<table>
<thead>
<tr>
<th>Sample No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Components Size (mm)</td>
<td>6.83</td>
<td>1.595</td>
<td>0.2135</td>
</tr>
<tr>
<td></td>
<td>4.83</td>
<td>0.8535</td>
<td>0.151</td>
</tr>
<tr>
<td></td>
<td>3.19</td>
<td>0.6035</td>
<td>0.1065</td>
</tr>
<tr>
<td></td>
<td>2.19</td>
<td>0.302</td>
<td>0.04525</td>
</tr>
</tbody>
</table>

Figure 4-2 Scanco Medical µCT100
(http://www.phenogenomics.dentistry.ubc.ca/equipment/MicroCTSpecimenScanner/)

4.2.2 Sample Preparation

The samples used were drain rocks with an average diameter of 0.75 inch (Figure 4-3). The samples were rinsed with tap water to remove the dirt followed by air dry. The original size did
not satisfy the requirement of the experiments, so size reduction was required. The cleaned rocks were sent for crushing using the cone crushers to reduce the particle size to about 5 mm. Part of the samples were then sent for grinding to further reduce the size. After size reduction, samples were sent for dry sieving to separate particles into different size fractions. 15 sieves, from No. 3.5 to No. 230, the opening of which were 0.0025 mm to 8 mm, were selected for size separation to produce narrow-sized particles of 14 different sizes (shown in Table 4-1). After size separation, all samples were placed in sealed bags for future use (Figure 4-3). These narrow-sized particles were mixed to prepare the poorly sorted samples (Table 4-2), and well sorted samples (Table 4-3). The mixing was done in a clean large basket to ensure that they were well blended.

Figure 4-3 Clear crush drain rocks (http://www.artsnursery.com/page/bulkgravelrock)

4.2.3 Experimental Apparatus

In the bulk density tests, the samples were packed into a designed test column of 3.75 inches in diameter and 5 inches in height (Figure 4-1). Computed tomography technique (CT) was also applied to generate a 3-D view of the packed rock. A micro-CT specimen scanner (Scanco Medical µCT100) was used (Figure 4.2), which allows for the non-invasive high-resolution 3D imaging of specimens up to 100 mm in diameter and 160 mm in length. The capability to scan results in an isotropic voxel size (i.e. nominal resolution) of 5 µm - 200 µm, and the acquired image stack are reconstructed into the slices with a thickness equal to the voxel size, generating
images in TIF or DCM format. Table 4-1, Table 4-2 and Table 4-3 show all the samples for porosity measurements. However, in CT imaging, scanning, reconstruction of images, as well as data analysis were time consuming. Hence, the samples tested in CT imaging were chosen after the results from bulk density were analyzed. Only representative samples were selected, which were shown in Table 4-4. Six out of the 14 narrow sized samples were selected, and one size range with different fractions of fine and coarse particles was selected to represent the poorly sorted sample. For well sorted samples, all three samples studied by the bulk density method was used for the CT imaging test.

Table 4-4 Specimen size and the corresponding sample holder size in CT scanning

<table>
<thead>
<tr>
<th>Specimen No.</th>
<th>Sample component (mm)</th>
<th>Average particle size in diameter (mm)</th>
<th>Sample holder size in diameter (mm)</th>
<th>Resolution in length (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100% 0.04525</td>
<td>0.04525</td>
<td>14</td>
<td>7.4</td>
</tr>
<tr>
<td>2</td>
<td>100% 0.1065</td>
<td>0.1065</td>
<td>14</td>
<td>7.4</td>
</tr>
<tr>
<td>3</td>
<td>100% 0.2135</td>
<td>0.2135</td>
<td>14</td>
<td>7.4</td>
</tr>
<tr>
<td>4</td>
<td>100% 0.6035</td>
<td>0.6035</td>
<td>14</td>
<td>7.4</td>
</tr>
<tr>
<td>5</td>
<td>100% 2.19</td>
<td>2.19</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>100% 6.83</td>
<td>6.83</td>
<td>48</td>
<td>24.6</td>
</tr>
<tr>
<td>7</td>
<td>25% 0.2135 &amp; 75% 2.19</td>
<td>1.6969</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>8</td>
<td>50% 0.2135 &amp; 50% 2.19</td>
<td>1.2</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>9</td>
<td>75% 0.2135 &amp; 25% 2.19</td>
<td>0.7076</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>25% 0.04525, 25% 0.1065</td>
<td>0.13975</td>
<td>14</td>
<td>7.4</td>
</tr>
<tr>
<td></td>
<td>25% 0.151, 25% 0.2135</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>25% 0.302, 25% 0.6035,</td>
<td>0.8385</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>25% 0.8535, 25% 1.595</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>25% 2.19, 25% 3.19, 25%</td>
<td>4.26</td>
<td>48</td>
<td>24.6</td>
</tr>
<tr>
<td></td>
<td>4.83, 25% 6.83</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
4.2.3 Experimental Procedures

(1) Porosity Measurements Using the Bulk Density Method

Porosities of samples with different particle size distributions were measured using the bulk density method under both loose random packing and close random packing conditions. The particles were packed into the test column by a scoop until the height of the upper level reached 4.1 inches, which was used to calculate the sample volume. The weight of the packed samples was measured by a scale with a 0.1g accuracy. During this process, no shaking or tapping was applied to the test column. Based on the equation $\rho = m/V$, the bulk density $\rho$ was calculated, which corresponded to the loose random packing condition.

The bulk densities under the close random packing condition were also measured. By tapping the wall of the test column and shaking the entire column, the particles in the test column were condensed. Particles were continuously added and tapped until there was not further decrease in the height of the packed rocks. By the same equation, the bulk densities under the close random packing condition were calculated. The solid density of the particles was measured to be 2.64 g/cm$^3$ by displacement of water. The porosity was calculated as $n = 1 - \frac{\text{bulk density}}{\text{solid density}}$. The bulk density tests for each sample type was repeated five times to improve accuracy. The porosity of the sample was set as the average porosity of each test.

(2) Porosity Derived from CT Imaging

Table 4-4 includes all the samples measured by the CT scanning method: six narrow-sized samples, three poorly sorted samples, and three well sorted samples. For each sample, a sample holder of an appropriate size was selected to minimize wall effects (Dirk et al., 1988). All samples used for the CT imaging was packed in the sample holder under close random packing condition. For each sample, 204 images taken from one detector position were obtained. Reconstruction of the images was conducted, and 50 of them which were continuous in length were imported as a stack to ImageJ. The distance between neighbor slices was the same as the voxel depth. The image processing procedures were similar to that used for 2-D image analysis introduced in Section 3.2.2. After image calibration and thresholding, the images were segmented into binary images consisting of the ore particles as background and pore space as foreground. Finally, a plugin called 3D objects counter was used to measure the volume of the
pores. The generated data was then exported to Microsoft Excel spreadsheets for further statistical analysis. In CT imaging, the results exported from ImageJ for each individual stack of images were the volume of individual pore. The total pore volume of a specific sample was calculated by summation, and the corresponding porosity was pore volume divided by the volume of the 50 images.

4.2.4 Possible Inaccuracy

In the sample preparation process, ore particles were washed by tap water to remove the impure followed by air dry. The huge amount of ores and the irregularity of the surfaces of the particles made it difficult to be washed thoroughly. Thus, there may be some fine ashes remaining. Besides, the limited time and space for air dry made the remaining of the capillary moisture content possible. In the particle separation part, agglomeration may happen during the dry sieving process, and the light-weight fine particles had the tendency to retain on the surface of the coarse particles which increased the fraction of coarse particles and decreased the fraction of fine particles. For tests related to mixture sizes, fine particles had a higher tendency to be blown away, resulting in the fraction change among components.

In column tests, bulk density under close random packing and loose random packing were both measured. During the packing process, when to stop adding samples was when the level of particles reached the mark of the column and the level did not shrink, while for loose random packing, ideally, there should be no shaking and no vibration. However, the action of adding samples lead to the vibration of the column which may result in the slumping of the packed layer and thus decrease the porosity. Besides, to measure the porosity under close random packed condition, tapping and shaking actions were applied to the column until the level was stable to the mark. However, the density of the rock layer was related to the number of times and the force applied for each time. For the tests related to mixture of particle sizes, particle size segregation may happen in the basket prior to the addition to the column, so the samples in the column may not critically obey the particle size distribution designed.

In CT imaging study, although great effort has been made to take the images using highest resolution allowed and to choose the images of the best quality, there existed some inaccuracy caused by the image quality and ImageJ program. First, with the restriction of the samples holder
diameter, the particles were difficult to distribute evenly and to achieve the close random packing condition, which may result in the change of the pore size distribution. Second, the image analysis program ImageJ may segmented the open pores into multiple isolated sub-pores, which decreased the percentage of large pores and increased the percentage of small pores. Third, the maximum storage of ImageJ limited the number of images imported to the program, which limited the thickness of the ore layers that can be analyzed.

4.3 Results and Discussion

4.3.1 Relationship between Porosity and Particle Size Distribution for Narrow-sized Particles

The relationship between porosity and particle size distribution was firstly investigated using narrow-sized particles. The narrow-sized particles used were collected between two sieves of neighboring sizes, and the size was defined as the average of the two sieve openings.

Figure 4-4 shows the relationship between porosity and particle size for narrow-sized particles measured by the bulk density method under loose random packing (left) and close random packing (right) conditions. In the case of loose random packing, the porosity decreased from over 50% to 40% when the particle size was increased from 0.04525 mm to 0.151 mm, after which the porosity remained almost constant at approximately 40% in the size range studied. Similarly, in the case of close random packing, the porosity decreased from 50% to 35% as the particle size was increased from 0.04525 mm to 0.151 mm, and remained constant afterwards. Even though the two packing methods generated the same trend that the porosity decreased at increasing particle size, the actual porosity values measured using the close random packing were lower than those measured using the loose random packing for the same particle size. In the close random packing, shaking would have reduced the volume taken up by the rock particles, thus allowing more particle grains to be added to the column. In other words, shaking increased the bulk density of the packed rock particles. These results suggested the importance of packing method, or stacking/dumping method in dump leaching and the construction of waste rock piles, in determination of porosity values.
Figure 4-4 The relationship between porosity and narrow particle size under loose random packing (left) and close random packing (right) derived from bulk density.

The porosity of the narrow-sized particles under close random packing was also measured by the CT scanning method. Figure 4-5 (left) shows an example of an 8-bit binary CT image of the cross section of the sample holder with the packed particles. The image was segmented with rock particles as the background in white and the pores as the foreground in dark. The cross sectional area studied was of a circular shape in the same diameter as the inner diameter of the cylindrical sample holder. The volume of individual pores was then measured by the 3D counter, which is a plugin of ImageJ. The total volume of pores divided by the inner volume of the sample holder gave the porosity values. The results are presented in Figure 4-5 (right), which showed that the porosity decreased with increasing particle size.

The results derived from these two methods were compared in Figure 4-6. In general, the two methods gave the similar trend that the porosity decreased as the particle size was increased. However, the porosity measured by the CT scanning method showed a continuous decreasing trend in the entire particle size range studied, while there was a critical particle size, above which the porosity no longer responded to the particle size variation.
Figure 4-5 8-bit binary image of the cross section of the samples consisting of narrow-sized particles in 2.19 mm after calibration and thresholding (left); the relationship between porosity and narrow particle size under close random packing derived from CT imaging (right)

Figure 4-6 Comparison of porosity of narrow size particles derived from bulk density and CT imaging

4.3.2 Relationship between Porosity and Poorly Sorted Particles

In dump leaching, run of mine ores without crushing are used to construct dumps prior to leaching. Thus, the ore particles in a dump under leach are typically of a wide size range. Such large variation in particle size also exists in the case of co-disposal of tailings and waste rock, which utilizes the void space in mine waste rock for the disposal of the fine grained tailings.
Therefore, it is essential to determine the relationship between porosity and particle size distribution for poorly sorted particles.

Samples to measure the porosity of poorly sorted particles were the mixtures of two different narrow-sized particles of increasing level of heterogeneity and with different compositions. The six combinations of the two narrow-sized particles of different compositions are shown in Figure 4-7. For a specific combination, five compositions of coarse and fine particles were used, starting with narrow-sized coarse particles and ended with narrow-sized fine particles. With the addition of fine particles, the porosity firstly decreased dramatically, followed by an increase when the fraction of fine particles was further increased. The higher degree of heterogeneity had a more pronounced impact on the shape of the porosity curve. For example, the magnitude of the porosity change was much more remarkable at the highest degree of heterogeneity, i.e., the combination of 6.83 mm and 0.04525 mm, than at the lowest degree of heterogeneity, i.e., the combination of 0.8535 mm and 0.6035 mm.

![Graph showing the relationship between porosity and particle size distribution](image)

Figure 4-7 The relationship between porosity and poorly sorted particle size under close random packing derived from bulk density

To verify the result, one combination, the mixtures of 0.2135 mm and 2.19 mm narrow-sized particles, was selected to do the CT scanning. Particles of 0.2135 mm in diameter and particles of 2.19 mm in diameter were mixed to conduct three tests with the mass ratio 1:3, 1:1, and 3:1. Figure 4-8 (left) shows an image of the cross section of the sample after the image calibration.
and thresholding. Figure 4-8 (right) presented the effect of the addition of fine particles into coarse particles on the porosity. With a small fraction of fine particles added to coarse particles, porosity decreased, while it increased when the fine particles exceeded a certain fraction. The trend of the curve was similar to that derived using the bulk density method. However, the bulk density method generated a more remarkable change in the porosity than the CT imaging did (Figure 4-9).

Figure 4-8 8-bit binary image of the cross section of the samples consisting of poorly sorted size particles with 50% 0.2135 mm & 50% 2.19 mm after calibration and thresholding (left); the relationship between porosity and the fraction of poorly sorted particle size under close random packing.
4.3.3 Relationship between Porosity and Well Sorted Particles

The results for the poorly sorted particles showed that as the difference in the size of the two components became smaller, the effect of fine particle addition on the porosity became less significant. This observation was supported by the porosity measurement of the well sorted particles. The well sorted particle samples were mixtures of particles in four neighboring sizes, with each size accounting for 25% by weight. The size of each sample was calculated as the average size of the four fractions. The effect of the average particle size on porosity was evaluated using both the bulk density and the CT scanning method.

Figure 4-10 (left) shows the porosity values derived using the bulk density method by loose random packing and by close random packing. In both cases, the porosity decreased as the average particle size was increased to a certain value, after which further increase in the average particle size no longer led to any change in the porosity within the particle size range tested. The results obtained using the CT scanning method were in agreement with those obtained using the bulk density method (Figure 4-10 (right)): as the average particle size was increased, the porosity decreased. However, the results by the CT scanning method seemed to show a consistent decreasing porosity as the average particle size was increased, even though the magnitude of the decrease was smaller when the average particle size was increased beyond a certain value.
Figure 4-10 Porosity of well sorted particle derived from bulk density (left); Comparison between porosity of well sorted particles derived from bulk density and CT scanning (right)

Comparing the case of the well sorted particles with the case of the narrow-sized particles (Figure 4-11) using both methods, it was observed that the well sorted particles behaved very similarly to the narrow-sized particles. In the case of the bulk density measurement (Figure 4-11 (left)), the trends of the porosity for the narrow-sized particles and the well sorted particles were similar, while the porosity of the well sorted particle mixtures were evidently smaller than that of the narrow-sized particles. The results derived using the CT imaging method (Figure 4-11 (right)) showed that the two curves followed each other closely, suggesting the same porosity trends in the case of the well sorted particles and the narrow-sized particles.
Figure 4-11 Comparison of porosity of narrow-size particles and well sorted particles derived from bulk density (left); Comparison of porosity of narrow size particles and well sorted particles from CT imaging (right)

4.3.4 Relationship between Porosity Distribution and Particle Size

The complex nature of the pore structure cannot be fully characterized by a single porosity value. Particle size distribution also plays a key role in determining pore size distribution, which was only qualitatively investigated in this study.

Figure 4-12 shows two images representing two vertical locations along the column for a narrow-sized sample made up of particles of 2.19 mm in diameter. The heterogeneity in the pore size distribution was not apparent in the case of the narrow-sized particles.

In contrast, Figure 4-13 shows the pore size distribution of samples of poorly sorted particles at two different vertical locations (left) and well sorted particles at two different locations (right). The poorly sorted sample consisted of 25% 0.2135 mm particles and 75% 2.19 mm particles, and the well sorted sample was made up of 25% 1.595 mm, 25% 0.8535 mm, 25% 0.6035 mm and 25% 0.302 mm particles. The well sorted particle showed a relatively uniform pore size distribution, while the different pore size distribution in both horizontal and vertical directions were visible. Conversely, in the case of the poorly sorted particles in a wide size range, the pore size distribution appeared very different and presented a high degree of variety. In particular,
particle segregation was observed. The image showed that the top right part only consisted of coarse particles and void space, while the bottom left part contained coarse particles, fine particles and void space. In the area of coarse particles, only pores of large size existed. In the bottom left part, fine particles were observed to fill the pores caused by the coarse particles. The heterogeneous geometric property of the particles and the variance of the particle size resulted in the heterogeneous distribution of the pores, and thereby affected the behavior of the fluid flow.

Figure 4-13 CT images of the cross section of a poorly sorted sample consisting of 25% 0.2135 mm particles and 75% 2.19 mm particles at two vertical positions (left) and a well sorted sample made up of 25% 1.595 mm, 25% 0.8535 mm, 25% 0.6035 mm and 25% 0.302 mm particles at two vertical positions (right)
4.4 Conclusion

The effect of particle size on porosity was studied using the bulk density and the CT-imaging methods in three cases: the narrow-sized particles, the well sorted particles, and the poorly sorted particles. For narrow size particles, the porosity measured by the bulk density method decreased as the particle size was increased up to 0.151 mm after which the porosity remained constant in the particle size range tested. The results obtained from the CT imaging showed a similar trend that the porosity decreased with increasing particle size, even though the critical particle size beyond which there was no further increase in the porosity was not observed using this method. For the well sorted particles, the influence of the particle size on the porosity was similar to that of the narrow-sized particles. The results obtained using the two methods were in agreement. For poorly sorted particles, the results obtained using the two methods porosity decreased as the fraction of the fine particles added was increased to a certain value, after which the porosity started to increase as the fraction of fine particles was further increased. In general, in the three cases studied, the two methods generated consistent results. The pore size distributions in three cases were also qualitatively studied using the CT imaging method. In the case of the narrow-sized and well sorted particles, a low level of heterogeneity in the pore size distribution was observed. In contrast, a high level of heterogeneity in the pore size distribution was observed in the case of the poorly sorted particles. Pore size segregation seemed to occur both horizontally and vertically. Fine particles were observed to be concentrated in some of the void spaces created by coarse particles. The pore size distribution results have an important implication for metal extraction from run of mine ores using dump leaching by influencing dump permeability and fluid flow paths.
Chapter 5. Conclusions and Future Work

The general objective of this research was to determine the particle size distribution in the highly heterogeneous packed ore beds and build the relationship between particle size distribution and porosity. The first objective was to determine the particle size distribution and spatial segregation of particle sizes in dump leaching. For this objective, the particle size distribution of the dump leaching pad at the case study mine was studied by analyzing the aerial images of multiple dump faces taken by a drone. The results showed that particles in the dump covered a wide range of sizes from less than 2 cm to larger than 200 cm in diameter. A spatial heterogeneity in the particle size distribution from the top to the toe of the dump was observed. This was attributed to the segregation of fine and coarse particles during the dump construction via end dumping, i.e., finer particles tended to be concentrated on the top of the dump and larger particles moved downward along the dump face. The spatial particle size segregation would have important implications for the chemical leaching in the dump leach pad. Meanwhile, the dump permeability, which seemed to be extremely high, increased with depth, suggesting that the spatial heterogeneity may cause preferential flow to occur.

The second objective was to quantify the effect of particle size distribution on porosity. For this objective, the porosities were studied by the bulk density and the CT-imaging techniques under three particle sorting conditions: narrow-sized particles, poorly sorted particles, and well sorted particles. For the narrow-sized particles, the porosity measured by the bulk density method decreased as the particle size was increased up to 0.151 mm after which the porosity remained constant in the particle size range tested. However, the results obtained from the CT imaging showed decreasing trend of the porosity with increasing particle size. For the well sorted particles, porosity derived from the two methods agreed with each other and the trend was similar to that derived from the narrow-sized particles. For the poorly sorted particles, the results obtained using the two methods porosity decreased as the fraction of the fine particles added was increased to a certain value, after which the porosity started to increase as the fraction of fine particles was further increased.

The findings of this study demonstrated the importance of characterization of particle size distribution in ore/rock piles for determination of fluid flow and the amounts of solutes leached.
In this study, although permeability was estimated by the Hazen formula, the direct model relating particle size distribution and permeability was not established. Even though porosities were quantitatively measured and pore size distributions were qualitatively evaluated, a model that predicts porosity and particle size distribution was not developed. Future work should focus on these two aspects.
Reference


Vuković, M., & Soro, A. (1992). *Determination of hydraulic conductivity of porous media from*
grain-size composition: Water Resources Pubns.