IMPROVING OPERATION AND PERFORMANCE OF CONTINUOUS VARIABLE DISCHARGE CONCENTRATOR

by

GIVEMORE SAKUHUNI

B.Sc., University of Zimbabwe, 2002
M.Eng. National University of Science and Technology, Zimbabwe, 2006

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Abstract

Continuous discharge centrifugal concentrators have been in use for more than 20 years but their technological advantages have not yet been fully exploited due to limited fundamental understanding of the technology and lack of operating strategy to efficiently adjust the multiple interacting variables to improve performance. In addition there is no mechanism for scale up and the existing laboratory procedures have limitations for predicting metallurgical response. This thesis focuses on two main goals. Firstly to develop a gravity amenability laboratory scale test procedure and secondly to develop a procedure for tuning CVD variables to improve operational performance with the aim of increasing application.

A novel optimization approach, code named NNREGA, integrating artificial neural networks, regression and a genetic algorithm, was developed and tested for tuning CVD operating variables to simultaneously maximize gold recovery and grade from a polymetallic flotation tailing. An optimum operating line was generated using a Pareto genetic algorithm. Results show that the procedure provides an efficient way of exploring the design space to learn the relationship between interacting variables and outputs and is capable of predicting an improvement in CVD performance. By generating the operating curves, the procedure provides a basis for CVD scale up. It also allows for continuous improvement and can be used as part of an operating strategy with potential to integrate into machine logic control.

A Gravity Release Analysis procedure, which consists of rougher, scavenger and four incremental cleaner laboratory scale Knelson concentrator stages was developed to characterize ore amenability to CVD concentration. The procedure was used to quantify gravity recoverable gold bearing sulphides in flotation tails from a massive sulphide ore and an epithermal gold vein ore. Results show good correlation between the laboratory procedure and CVD, with the laboratory procedure results forming an upper limit for the CVD. Thus, the Gravity Release Analysis procedure can be used to predict potential CVD application and to benchmark operating machines. Based on the Gravity Release Analysis procedure, a mechanism of quantifying gravity amenability and gravity kinetics, the gravity release index, was introduced. The index can be used to quantify the relative abundance of different gravity recoverable mineral species in an ore.
Preface

The author, in consultation with the research supervisor Dr. Bern Klein, carried out the definition and design of the research program, the analysis of experimental data and preparation of the thesis manuscript. Apart from the chemical and X-Ray diffraction analyses, which were done by commercial laboratories, all the experimental work involved was carried out 100 % by the author of this thesis.

A version of chapters 4 and 5 has been submitted for publication under the title “A novel hybrid evolutionary performance improvement procedure for optimization of multivariate processes” with myself as primary author and Dr. Bern Klein & Dr. Emre Altun as co-authors.
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<th>Description</th>
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<tbody>
<tr>
<td>ANN</td>
<td>Artificial neural networks</td>
</tr>
<tr>
<td>BS</td>
<td>Bowl speed, which is the rotational speed of the centrifugal concentrator</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic algorithm</td>
</tr>
<tr>
<td>CCCD</td>
<td>Circumscribed central composite design</td>
</tr>
<tr>
<td>CVD</td>
<td>Continuous Variable Discharge concentrator</td>
</tr>
<tr>
<td>CVD6</td>
<td>Pilot scale 6-inch bowl CVD</td>
</tr>
<tr>
<td>OVP</td>
<td>Operating variable performance</td>
</tr>
<tr>
<td>GRG</td>
<td>Gravity recoverable gold</td>
</tr>
<tr>
<td>GAT</td>
<td>Gravity amenability tests</td>
</tr>
<tr>
<td>GRA</td>
<td>Gravity Release Analysis</td>
</tr>
<tr>
<td>NNREGA</td>
<td>The hybrid optimization approach, integrating ANN, regression and GA</td>
</tr>
<tr>
<td>GRGS</td>
<td>Gravity recoverable gold bearing sulphides</td>
</tr>
<tr>
<td>LM</td>
<td>Levenberg Marquardt</td>
</tr>
<tr>
<td>GRI</td>
<td>Gravity Release Index</td>
</tr>
<tr>
<td>GRA</td>
<td>Gravity Release Analysis</td>
</tr>
<tr>
<td>GRG</td>
<td>Gravity Recoverable Gold</td>
</tr>
<tr>
<td>SEM</td>
<td>Scanning Electron Microscopy</td>
</tr>
<tr>
<td>EDX</td>
<td>Energy Dispersive X-ray Spectroscopy</td>
</tr>
<tr>
<td>MD3</td>
<td>Laboratory scale 3-inch Knelson concentrator</td>
</tr>
<tr>
<td>LKC</td>
<td>Laboratory Knelson Concentrator (MD3)</td>
</tr>
<tr>
<td>NSGA II</td>
<td>Non dominated sorting genetic algorithm</td>
</tr>
<tr>
<td>CDCCs</td>
<td>Continuous discharge centrifugal concentrators</td>
</tr>
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Dedication

To my Dad and Mom: just to say thank you for your labour of love and sacrifice. The Lord God, He is faithful and alive. May all the glory be to Jesus Christ.

To the Loving memory of my dear sister Sophia Sakuhuni, and father-in law Va Chigodora, you will always be missed

To my wife Loyce and our kids: Nyasha and Takudzwa, you have been a wonderful team. I dedicate this dissertation to you, this is just the beginning, and the way has been paved.
Chapter 1: Introduction

1.1 Background

Gravity concentration is a mature technology with a variety of concentrating devices in operation today. The processes have evolved from machines that use unit gravity such as sluices and spirals to batch enhanced (centrifugal) concentrators and most recently to continuous centrifugal concentrators. The motivation for the batch enhanced gravity concentrators was to recover fine gold lost to plant tails (Napier-Munn, 1997). This led to the advent of the two most dominant modern commercial batch centrifugal concentrators (BCCs) - the Falcon and Knelson concentrators. These are widely employed to recover free gold in hard rock mining operations and to a lesser extent alluvial gold. However, obligatory stop-start cycles of these batch processes dramatically diminished their efficiency and profitability for applications when product mass yields exceed ~0.1 %. The continuous discharge centrifugal concentrators (CDCCs) introduced in the early 1990’s offer substantial technological and economical advantages for applications with mass yield exceeding 0.1 %; however these technologies have never been widely employed nor have they been subjected to rigorous optimization assessment.

There are four main types of CDCCs, namely Knelson Continuous Variable Discharge (CVD), Falcon C concentrator, Kelsey Jig and Multi Gravity Separator (MGS). These machines offer the same advantages over unit gravity machines, as their batch-scale siblings with respect to the ability to separate particles based on density difference under conditions of high centrifugal acceleration. Despite this advantage, the number of commercial installations shows that CDCCs are not widely used. Data obtained from the technology vendor in 2009 showed there were only 62 commercial installations of the CVD in 13 countries, compared to over 2000 Knelson batch type machines in over 70 countries. About 53 % of these installations are in gold/gold sulphide operations mostly in Russia and Kazakhstan. Six installations are in chromite and ferrochrome, nine in tungsten and molybdenum and one installation in each of tantalum, iron, talc, tin and metal recycling. Only four of the commercial units are installed in Canada (host of the technology) 2 units at a technology centre, 1 in Fe/talc processing and one in tungsten.

The limited applications can be attributed to lack of fundamental understanding (Majumder & Barnwal, 2006) and to inadequate information demonstrating the technical advantages of the technologies and the corresponding economic benefits. The risk of adopting new and unfamiliar
technologies is averse to mineral processing engineers due to high risk associated with start-up problems. About 40 - 61 % of start-up difficulties are attributed to equipment (scale up, selection and materials) (Holroyd, 1967). Figure 1.1 shows how the maturity of a technology and complexity of flowsheet influences the success of start-ups. Slow (type 4) start-ups, as shown in Figure 1.1, which are associated with newer technologies, have serious implications to mining projects and investment, the worst being shut down or failure of the process and perhaps, the mine itself. Engineers often prefer to use proven technologies; rather than venture into unfamiliar territory, particularly with the many complexities associated with ore characteristics. Mining companies are unwilling to try new technologies, which may result in financial loss.

![Conceptual start up curves](image)

**Figure 1.1: Conceptual start up curves (McNulty, 1998).**

Table 1.1 summarizes the main operating variables and principles for each of the continuous centrifugal concentrators. CDCCs have multiple operating variables leading to flexibility with concentrate mass yields typically 1 - 50 %. Applications include base metal and precious metal-bearing sulphides, tungsten, tin, tantalum, chromite and molybdenum. A more complete review and comparison of these machines can be found elsewhere in the literature (Luttrell, Honaker, & Phillips, 1995); Laplante, 2001; McLeavy, 2005; Majumder and Barnwal, 2006; Ghaffari, 2004; Honaker and Das, 2004).
Table 1.1: Summary of CDCCs operating variables.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Operating Principle</th>
<th>Machine Parameters</th>
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<tr>
<td>Falcon C</td>
<td>Sluicing/Reichert Cone</td>
<td>applied centrifugal force,</td>
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<td></td>
<td>-(Laplante et al., 1994);</td>
<td>concentrate valve diameter</td>
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<td></td>
<td>-(Majumder and Barnwal, 2006)</td>
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<tr>
<td>CVD</td>
<td>Fluidized bed</td>
<td>applied centrifugal force,</td>
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<td></td>
<td>-(Honaker and Das, 2004),</td>
<td>pinch valve open time,</td>
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<td></td>
<td>- (Majumder and Barnwal, 2006)</td>
<td>pinch valve closed time,</td>
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<td></td>
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<td>fluidization water flow rate</td>
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<td>MGS</td>
<td>Shaking Table</td>
<td>drum speed,</td>
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<td></td>
<td>-(Majumder and Barnwal, 2006)</td>
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<td>shake amplitude,</td>
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<td>wash water flow rate</td>
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<td>Kelsey Jig</td>
<td>Jigging</td>
<td>pulse frequency,</td>
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<td>concentrate orifice diameter</td>
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To date there is a lack of experience and knowledge about operating these machines. An operator does not know if the CDCC is operating at optimum conditions and they do not know how to efficiently adjust the interacting operational variables to improve metallurgical performance. For the CVD, each machine is unique due to variations in the pneumatic system, and every time a machine is installed there is a need to determine the set points. There is therefore need to bridge the gap between innovation and application. While multiple variables may enhance flexibility in application of CDCCs, interactions of operating variables presents complexity to operators, which can contribute to shunning of the technology. In addition, there are no laboratory scale continuous centrifugal machines, making it difficult to assess potential application. Currently, evaluation of the CVD is generally achieved through pilot scale testing using a CVD6 (6” bowl diameter), which has a throughput of about 1tph. Testing involves selecting operating
variable levels to achieve “optimum” product grade and recovery by varying one variable at a time. This technique can be misleading when there are multiple interacting operating variables (Altun et al., 2006) leading to operating the CVD at sub-optimum variable settings. The development of a dependable, low cost time saving strategy for assessing performance of any unit operation in mineral processing is crucial, where such testing normally involves rigorous and costly laboratory, pilot and full scale trials.

The first goal of this thesis is to advance CVD technology by developing an efficient approach to tune the CVD control variables, in order to achieve optimum metallurgical performance with the aim of providing a tool for commissioning, auditing and making continuous improvement. This research builds on the work by McLeavy (2005) which focused on demonstrating the impact of operating variables on the separation performance of the CVD. He identified 8 potential factors that influence CVD performance which include: fluidization flow rate, % solids, feed grade, particle size, bowl speed (BS), pinch valve open duration (PVO), pinch valve closed duration (PVC) and solids feed rate. By using a sixteen-run fractional factorial design on a quartz/magnetite synthetic ore to screen the variables, he identified (BS, PVO and PVC) as the main machine variables. Whilst there still remains a need to develop a sound phenomenological or mechanistic CVD model, this is beyond the scope of the current research thus the models used in this study are empirical. The results are expected to provide insight into the separation mechanism of the CVD. The second goal is to develop an indicative bench scale test that can be used to assess potential CVD applications.

1.2 Research objectives
The specific objectives of this thesis are:

1. To develop a bench scale test to predict applicability of CVD
2. To develop a process optimization approach that considers more than one performance objective
3. To develop a novel approach to select operating conditions that optimize performance for a CVD
4. To provide clarity on the interaction between control parameters and performance indicators
1.3 Structure of the thesis

The thesis consists of 6 chapters:

Chapter 1 introduces the background of the research project, its objectives and the structure of the thesis.

Chapter 2 reviews the literature on centrifugal separation, optimization procedures and details the basis for selecting the optimization approach used in this research.

Chapter 3 reviews existing laboratory procedures used to assess gravity amenability and introduces the Gravity Release Analysis as a laboratory procedure for predicting potential CVD application and benchmarking operating CVDs.

Chapter 4 describes the NNREGA approach and how it was developed.

Chapter 5 shows CVD pilot and full-scale results obtained from testing the NNREGA approach on Myra Falls flotation tailings.

Chapter 6 outlines the mains contributions and recommendations for future work.
Chapter 2: Literature review

This chapter reviews centrifugal concentration with emphasis on the CVD, modeling and optimization approaches considered suitable for CVD optimization.

2.1 Theory of centrifugal separation

Gravity concentration is the oldest mineral processing technology only preceded by hand picking, but there is still no unified theory for the technology (Burt, 1984). Centrifugal concentration, which came into use in the late 1860s mainly in California, and only became a dominant force in mineral processing in the late 1980s, with the introduction of wear resistance material (Ling, 1998), has revived considerable research interest for gravity concentration as evidenced by the volumes of publications. However, a fundamental understanding of the mechanism of concentration is still to be developed.

According to Majumder & Barnwal (2006) much of centrifugal theory is from sedimentation theory, with Svedberg and Pederson’s 1940 theories forming the basis, however, the first scientific study on the application of centrifugal force in mineral processing was done by Ferrara (1960) using a rotating Perspex tube. Whilst mineral processing centrifuges have a distinct operation niche, the mode of particle segregation is similar to conventional centrifugal settling machines. In design, the Knelson and Falcon concentrators look much the same as the basket type centrifugal filter, whilst the MGS looks like the multistage push type filter (Hsu, 1981). It is therefore imperative to derive knowledge of the operation of mineral processing centrifuges from their conventional counterparts.

Majumder & Barnwal (2006) reviewed the status of centrifugal concentration technology and noted the lack of fundamental studies on the mechanism of concentration of all the existing technologies. In agreement with Hsu (1981), these authors proposed that centrifugal phenomena can completely be specified by a combination of the continuity equation with an appropriate flux in a centrifugal force field, and the equations of motion in a steady rotational field with appropriate boundary conditions. In its simplest form, centrifugal separation is a result of different solid particles suspended in a less dense liquid and subjected to a centrifugal force field. The particles migrate through the liquid at varying velocities, which are a function of particle shape, specific density, size, mass, liquid density and viscosity. The centrifugal force field serves to increase the rate of particle sedimentation. Considering a particle of mass (m) revolving at a radius (r) with an
angular velocity (ω), it is subjected to a centrifugal force \( F_c = mr\omega^2 \) in a radial direction and a gravitational force \( F_g = mg \) in a vertical direction. The separation power of a centrifuge (Eqn. 2.0) is the ratio of centrifugal to gravitational force.

\[
g_c = \frac{\omega^2 r}{g} \tag{2.0}
\]

Newton’s second law of motion in a centrifugal field gives the sum of the forces acting on the particle \( i \).

\[
F_i = m_i \frac{d^2r_i}{dt^2} \tag{2.1}
\]

The net change relative to the space-fixed coordinate system is a result of particle acceleration, Coriolis and centrifugal field effects. And the force \( F_i \) consists of buoyancy (which is a function of particle volume and centrifugal acceleration) and drag force (Stoke’s resistance). According to Hsu (1981) the equation of motion for centrifugal sedimentation for a spherical particle is:

\[
-\left( \frac{18\mu}{(\rho_p - \rho_f)D_p^2} \right) v = \left( \frac{\rho_p}{(\rho_p - \rho_f)} \right) \frac{dv}{dt} + 2\left( \frac{\rho_p}{(\rho_p - \rho_f)} \right) \omega \times v + \omega \times (\omega \times r) \tag{2.2}
\]

Where \( \mu \) and \( \rho_f \) are fluid viscosity and density respectively expressed as a function of radial distance from the rotating axis; \( D_p \) and \( \rho_p \) are particle diameter and particle density respectively.

For a particle in an in-compressive fluid and neglecting the Coriolis effect, the equation of motion reduces to (Hsu, 1981):

\[
\frac{dv}{dt} + \frac{18\mu}{\rho_p D_p^2} v = \frac{\omega^2 r}{\rho_p} [\rho_p - \rho_f] \tag{2.3}
\]

When settling takes place in the Stokes range, \( Re < 0.4 \), the terminal velocity is derived by equating the acceleration to zero such that Eqn. 2.3 reduces to:

\[
v = \frac{(\rho_p - \rho_f)D_p^2 \omega^2 r}{18\mu} \tag{2.4}
\]

If particle size is large such that the terminal velocity is no longer in the Stoke’s region, the mechanics of particle movement through a fluid has to be applied for steady flow of a fluid passing
a solid particle. Boundary layers are established and a force $F_D$, which is a combination of boundary layer drag and form drag expressed by Eqn. 2.5, is exerted on the particle by the fluid.

$$F_D = \frac{C_D \rho_p v^2}{2}$$  \hspace{1cm} \text{(2.5)}

Where $v$ is the free stream velocity relative to the particle, $C_D$ is the drag coefficient, which depends on the Reynolds number (Re) (Hsu, 1981) given by:

$$\text{Re} = \frac{D_p \rho_p v}{\mu}$$  \hspace{1cm} \text{(2.6)}

For spherical particles in the 3 flow regions, the drag coefficient is given by:

$$C_D = \frac{24}{\text{Re}} \hspace{1cm} \text{Re < 0.4 (Stoke’s region)}$$

$$C_D = \left(\frac{10}{\text{Re}}\right)^2 \hspace{1cm} 0.4 < \text{Re} < 500 \text{ (Allen region)}$$

$$C_D = 0.44 \hspace{1cm} 500 < \text{Re} < 200000 \text{ (Newton region)}$$

The relationship between particle settling velocity in centrifugal force field and gravitational force field is obtained by combining equations 2.0 and 2.4 yielding equations 2.7 (a) for Stoke’s, (b) Allen’s and (c) for Newton’s region (Hsu, 1981; Klein, 1992):

$$v_c = G v_g$$  \hspace{1cm} \text{(2.7a)}

$$v_c = G^{1/2} v_g$$  \hspace{1cm} \text{(2.7b)}

$$v_c = G^{1/3} v_g$$  \hspace{1cm} \text{(2.7c)}

where $v_c$ is the terminal velocity in a centrifugal force field and $v_g$ is the terminal velocity in a gravitational force field. The equations show that, the effect of centrifugal velocity on particle settling is more dominant in the Stoke’s region implying that high centrifugal force has more significant effect for fines separations where viscous forces dominate inertial. However, particles in a centrifuge never reach a terminal velocity (Coulson, 1990), and the maximum radial settling velocity is used for comparison instead (Ling, 1998).

Ling (1998) conducted computational studies on a batch Knelson concentrator based on tungsten, magnetite and silica which showed that very fine dense particles were recoverable by the Knelson concentrator despite the extremely large difference in maximum settling velocity between coarse and fine dense (tungsten or magnetite) particles. As a result he concluded that centrifugal
settling alone was inadequate to explain the separation observed in a Knelson concentrator. He therefore proposed radial migration and percolation under centrifugal force to be additional mechanisms involved in particle separation. Figure 2.1 is based on the findings of Ling (1998), which summarizes the relationship between particle size and settling velocity, showing how centrifugal force amplifies the settling velocity difference between heavy and light particles, especially for the coarser fractions according to

![Figure 2.1: Variation in settling velocity with particle size and the influence of centrifugal force, (Ling, 1998).](image)

Huang (1996) observed that light silica reported to the outside of the Knelson concentrate bed whilst the heavier fractions (magnetite), reported on the inside, which is characteristic of bed inversion (Epstein, 2005). Thus, the heavy particles reporting to the concentrate of a centrifugal concentrator have to sink through a bed of light gangue after being captured. Voidage plays a big role for either small particles draining through a bed of coarse bulk particles (percolation) or large particles passing a bed of small bulk particles (migration). Koppalkar (2009) observed that fine tungsten recovery was higher for a fine gangue particle bed compared to a coarser bed, by determining the degree of tungsten recovery in a bed of silica gangue of different particle sizes (425, 212 and 106) microns, in a fluidized chamber, in a gravitational force field. He concluded that resistance of gangue to tungsten percolation could not be explained by voidage only but also gangue density and particle size. When counter current fluidization is involved, small spherical low-density particles are more easily fluidized. In addition to the intensity of the centrifugal force
field, other factors affecting percolation and migration, and therefore centrifugal concentration in a Continuous Variable Discharge concentrator are; particle size and density of bed, voidage of separation zone, momentum of moving particles, the degree of fluidization and the residence time of particles in the concentration ring.

Although this analysis helps in understanding the effect of different factors on centrifugal separation, it is still incomplete as a basis of fundamentally describing the mechanism of particle separation in centrifugal concentrators.

2.2 The Continuous Variable Discharge (CVD) concentrator

The CVD consist of a rotating bowl with stepped, inclined walls mounted on a rotor assembly that is driven by a variable speed motor. Water is injected into the concentrate ring through a series of fluidization holes. A stationary feed pipe introduces the feed into the centre of the bowl. The feed hits the bottom of the rotating bowl and is deflected up the bowl wall, with differential initial acceleration as a possible mode of initial separation. Figures 2.2 and 2.3 show the main features of the CVD.

![Figure 2.2: CVD cross-section showing the rotor assembly, air and fluidisation water lines and pinch valves.](image-url)
Particle separation in a CVD occurs in two zones: the short cone and the concentrate ring shown in Figure 2.2 (McLeavy, 2005). Whilst differential-settling rates can be the mode of separation as particles migrate along the short cone, it cannot fully describe upgrading that occurs in the concentrate ring where fluidization is involved. Stratification by both density and particle size occurs as slurry travels up the short cone of the bowl and a superficial velocity ring splits the stratified bed prior to entering the concentrate ring. Further upgrading occurs in the concentrate ring as the partially stratified bed of particles is contacted by fluidization water. Timed opening of pinch valves located around the concentrate ring allows for continuous discharge of concentrates and the light particles overflow the bowl into a tailings launder. The extent and contribution of each mechanism and the consequent dependence on control parameters is still to be fully understood.

2.2.1 Particle motion in the CVD

As particles enter the CVD they are deflected to the walls of the rotating cone (bowl). The change in velocity (both magnitude and direction) is a function of both centrifugal acceleration ($r\omega^2$) and particle density ($\rho_p$) and fluid density ($\rho_f$) as shown in Eqn. 2.8, such that heavier particles get to the bowl wall first.
\[
\frac{dx}{dt} = \left[1 - \frac{\rho_f}{\rho_p}\right] r \omega^2
\]

According to Ungarish (1993) when a fluid is spun up from rest in a rotating cylindrical container, three flow regimes result: a shrinking non rotating inner region (a), an expanding partially spun-up outer layer (c) and an Ekman shear layer (b) which draws fluid from region I and feeds it into the spinning region III as shown in Figure 2.4.

![Figure 2.4: The three flow regions in a spin up from rest (side and top view) (Ungarish, 1993).](image)

For a laboratory scale Knelson concentrator, Ling (1998) proposed two zones in the radial direction; a dilute zone consisting of only very fine light particles and a separation zone between the dilute zone and the middle section of the concentrate bed consisting of an outer layer of the flowing slurry and the inner section of the concentrate bed shown in Figure 2.5. This provides insight on possible particle movement and separation in the CVD short cone.
Unlike the Falcon C concentrator, referred to as a centrifugal sluice by Luttrell et al. (1995), the CVD bowl walls are stepped and inclined at an angle (25° for CVD6 and 15° for other models). This makes it difficult to predict the motion of particles as they travel up the short cone in the CVD. However, a lot can be derived from the operating mechanism of the Falcon C. Although bowl design is crucial to separation mechanism as it is the means by which the force generated by rotation is split into two components, one normal to the bowl and responsible for bed stratification the other parallel to the bowl wall and responsible for particle migration, its contribution is still not fully understood (Majumder & Barnwal, 2006). The walls of the Falcon C unit concentrator are inclined and smooth and it is easier to predict the path taken by particles. In the Falcon C, centrifugal force is resolved into two components, a strong force normal to the bowl wall responsible for stratification of particles as they move up the migration zone (Honaker, Wang, & Ho, 1996) and a weaker component parallel to the bowl wall pushing the stratified bed towards the top of the unit.

Buivino (1993) proposed that for a non-fluidized Falcon B concentrator, coarse particles are recovered by migration, burying them into the concentrate bed, whilst fine particles are recovered by percolation, lodging into the interstices. Laplante et al. (1994) proposed a two stage process; the initial step being movement of dense particles to the slurry interface and concentrate bed, which is a function of feed rate, followed by capture of dense particles in the concentrate bed,
which is independent of the feed rate. Stratification along the short cone is a function of both particle density and particle size. Holtham (1992) reviewed particle transport in sediment transport systems, including spiral, pinched sluice and Reichert cone, using the Bagnold effect to explain particle separation by density and size. Similar to Ungarish (1993), he proposed three modes of transport; rolling (for large heavy particle), saltation (trajectory motion) and suspensive (either by eddy currents or particle-particle interaction. It can be postulated that 100 % of the particles in the rolling mode, ± 50 % of those in saltation mode and a small fraction of the particles in suspensive mode report to the concentration ring. It can also be inferred that the proportion of particles in suspensive mode reporting to concentrate ring is proportional to the water split to concentrates. For a heterogeneous bed, particles will have different transport modes due to differences in size and density, although the shear velocity at any point is the same. It is critical to note that particles in suspension mode are poorly classified and efficient separation only occurs in the saltation zone. Kroll-Rabotin et al (2010) used the saltation mode to model particle separation in a Falcon C and derived a partition function from fluid flow simulations for fine particle separation.

Stratification occurs in a similar fashion in the CVD; however, the stepped bowl makes it difficult to predict the actual path taken by particles, and the timed opening and closing of the pinch valves tends to disturb the concentrate bed, further complicating the separation mechanism. It can be postulated that the design enables material to undergo multiple concentration stages, and particles are subjected to increasing centrifugal force at each successive stage as they move up the concentrating bowl ( Majumder, Tiwari, & Barnwal, 2007). The resultant stratified bed consists of large and small dense particles (a result of consolidated trickling) in contact with the bowl wall. However, tests conducted by Huang (1996) using a separable batch Knelson bowl showed that tungsten (heavy) particles were recovered on the surface of the concentrate bed instead of the bowl wall as expected. He concluded that upgrading of tungsten particles from the gangue (silica) takes place at the surface of the rings and depended on the competing forces, acceleration of the consolidated trickling and the bulk density of the separation zone. This observation can be explained by the effect of inertial and frictional forces between the wall and the outer layer reducing the vertical velocity of these particles such that those in the inner layers arrive and enter the concentration ring first. Alternatively the bed inversion effect Escudié et al (2006) caused by fluidization maybe be attributed to the observation.
A partially stratified bed therefore enters the concentration ring that is initially completely fluidized, without any solids. A bed of particles builds up and the concentrating ring becomes partially fluidized. The particle bed is kept dilating by a combination of fluidization water pressure and shear induced dispersive forces (Huang, 1996; Holtham, 1992; Kelly & Spottiswood 1982). For the CVD, timed pinch valve opening allows for upgraded material in the concentration ring to exit the CVD into the concentrate launder. Whether a particle will report to the concentrate or tailing depends on both machine and ore variables. Previous work suggested that pinch valve timing, rotation speed of the concentrating bowl (bowl speed), and fluidization water pressure are the main machine variables that affect particle separation for the CVD (Klein et al., 2010; McLeavy, 2005; Ghaffari, 2004).

### 2.2.2 Fluidization

One of the distinct features between the Falcon C and Knelson CVD is the absence of fluidization in the Falcon C retention zone. The Falcon C does not use fluidization water and some researchers including the owner of the technology claim it performs better at separating fines (McAlister & Armstrong, 1998; Deveau, 2006). Kroll-Rabotin et al (2010) argued that forced fluidization would most likely re-suspend the whole bed, which will be of little to no benefit in improving concentration efficiency of fine particles. The CVD has a fluidized concentrate ring which serves to dilate the bed, preventing compaction and enabling mass transfer between material subsequently entering the ring and that already in the ring (Abela, 1997; Majumder & Barnwal, 2006; Laplante & Shu, 1993; Ancia et al., 1997). In addition, fluidization helps to avoid plugging of the concentrate outlet by assisting particles to flow from the bed into the pinch valves (McLeavy, 2005). At high bowl speed, solid particles tend to displace water which flows to the centre of the bowl, therefore higher fluidization is necessary when operating the CVD at high bowl speeds or when concentrating coarse dense particles (Mcleavy et al., 2001).

Although liquid fluidization or teeter bed particle classification has a long history in mineral processing (Epstein, 2005), its applicability to centrifugal concentration has not been fully assessed. Most of the research on teeter beds has been conducted in a gravitational field which is easy to measure and regulate the parameters affecting particle separation (Jean & Fan, 1986; Moritomi et al., 1982; Epstein, 2005; Escudié et al., 2006). A key finding of these tests is the effect of fluidization (liquid) velocity on the segregation of particles of mixed species, which is termed bed inversion. The inversion point is when the fluidization velocity is such that the bed is perfectly
mixed to the extent that beyond this level the increase in voidage causes gravitational sizing to dominate sorting. Figure 2.8 shows how increasing fluidisation velocity affects particle segregation for binary particles of different density and size.

![Diagram showing effect of fluidisation velocity on sizing and sorting](image)

Figure 2.6: The effect of fluidisation velocity on sizing and sorting, showing the inversion point. The darkened and open circles represent small higher density and large light particles respectively (Epstein, 2005).

According to Epstein (2005), the mineral processing rule of thumb that sizing is best performed under free settling conditions whilst sorting is performed under hindered settling, is based on the bed inversion phenomenon. By using normalised bulk density as a measure of the driving force for particle segregation, he investigated the effect of increasing fluidisation velocity on sorting and sizing in a gravitational field. He observed that particle segregation as a result of sizing increases with voidage (fluidisation velocity), whilst particle segregation due to sorting decreases with increasing voidage. Below the inversion point, voidage is low and gravitational sorting dominates sizing and the inverse is true above the inversion point. The theoretical treatment from powder technology publications (Jean & Fan, 1986; Moritomi et al., 1982; Epstein, 2005; Escudié et al., 2006), and specifically the work of Epstein and others, aides understanding on the balance between size and density classification by the CVD observed by Klein et al (2010). For centrifugal concentrators, however, there is no consensus among researchers on whether the
fluidization water velocity is adequate to fluidize the particle bed in a centrifugal force field. The general understanding is that the particulate bed still remains packed and the fluidization water merely percolates the packed particle bed causing bed dilation and aiding in particle mobility through the pinch valves reducing plugging of the holes. Honaker (2006) however, suggested that the mechanism of particle separation in a CVD was based on the teeter bed effect, indirectly implied by other authors (Majumder & Barnwal, 2006; Ancia et al., 1997; McLeavy, 2005). If this assertion holds, then in a CVD, the suspended particle bed forms a virtual heavy media with an apparent specific gravity (S.G.) determined by the bed composition. Particles arriving at the bed surface either enter the bed or are rejected to the overflow depending on their specific density. The apparent density of the fluidized bed depends on both fluidization water velocity and the proportion of heavy particles in the bed. Increasing fluidization velocity lowers the apparent bed density such that lighter particles are retained in concentrate, lowering the grade. There exists a critical fluidization flow rate below which increasing water flow rate increases both grade and recovery and above which a gradual decrease in the concentrate grade takes place as observed by Mcleavy et al (2001) and McLeavy (2005). Whether this critical fluidization coincides with the bed inversion velocity is still to be determined.

The actual contribution of fluidization to mineral upgrading in a centrifugal concentrator is still to be fully understood (Majumder & Barnwal, 2006). In this research, the fluidization water flow rate was maintained constant at 8 gal/min, considered optimal for the CVD6 (McLeavy, 2005) and 3170 gal/min for the CVD42, recommended by the manufacturer. The fluidisation water pressure, which is a function of fluidisation velocity and bowl speed, is to be calibrated when the machine is still new and used to monitor the machine for blockages of the fluidisation holes, but it is unreliable as a measure of flow rate.

2.2.3 Bowl speed

The contribution of bowl speed (rotational speed of the concentrating bowl) on centrifugal concentration is to increase the intensity of the force field exerted on particles from the conventional gravitational force field. The rotation rate is thus quoted in g, a multiple of gravitational acceleration (= 9.8 m/s²). For the CVD6 the vendor recommended bowl speed ranges from 600-1030 rpm, which corresponds to 30-90 g. Conversion from rpm to g-Force is by:
\[ g - \text{Force} = \frac{d\omega^2}{70414} \quad 2.9 \]

where \( d \) is the diameter of the CVD bowl in inches, \( \omega^2 \) is the bowl speed in rpm.

The effect of bowl speed on CVD concentration can be best understood by substituting for centrifugal acceleration in Stokes’ equation (see Eq. 2.4): Three main variables influence the settling velocity (\( v_s \)) the centrifugal acceleration, particle diameter (\( d \)) and specific gravity (S.G.). Increasing the bowl speed increases the effective centrifugal force causing a reduction in separation density and an increase in the difference in settling velocities of particles. A reduction in separation density results in dilution of the high specific density product by lower density particles (McLeavy et al., 2001).

The effect of centrifugal force on separation cannot be generalized for all centrifuges. For instance, the Falcon C running at 300 g is reported to perform well at fines separation (Kroll-Rabotin et al., 2010). The Chinese SL type continuous concentrator is known to operate at high rotation speeds up to 660 g, and is reportedly efficient at recovering fine cassiterite, although the throughput is significantly reduced for slimes recovery (Ling, 1998). The MGS has been found to give good upgrading of fines down to 10 microns, using a centrifugal acceleration of 22 g (Burt, 1999). It is necessary to assess the effect of bowl speed on CVD separation in order to examine possible ultra fine separation potential and enhance the understanding on how bowl speed increases the separation power of a centrifugal mineral separator.

Considering the two upgrading zones in a CVD, increasing bowl speed would increase stratification in the short bowl while causing bed compaction within the concentrate ring and inhibiting further upgrading. A threshold bowl speed thus exists, which maximizes stratification without compacting the bed. McLeavy et al (2001) found this occurred around 43 g for the ore they tested using the CVD6. This research assesses CVD performance over the feasible operational range.

### 2.2.4 Pinch valve closed duration

Upgrading in the concentrate ring is a function of pinch valve timing, bowl speed and fluidization water flow rate. The presence of a superficial velocity ring covering the concentrate ring limits the amount of particles that can be retained per unit time in the ring. Increasing the pinch valve closed duration increases the time for heavy particles to displace lighter ones thus
increasing the concentrate grade whilst lowering recovery as heavy particles are rejected due to no capacity for retention and bed erosion (McLeavy et al., 2001; McLeavy, 2005; Klein et al., 2010).

From Figure 2.7, it is evident that there is a limit above which increasing pinch valve closed duration will not further reduce recovery. It is worth noting that different machines have different operating ranges for pinch valve timing which is attributable to variations in the pneumatic system due to differences in both the fabrication material and length of air lines. Since no two machines are identical, there is need to determine set points for each machine prior to use.

![Figure 2.7: The effect of pinch valve closed duration on mass yield and gold recovery (Klein et al., 2010).](image)

2.2.5 Pinch valve open duration

Reducing pinch valve open duration increases upgrading whilst increasing the open time increases recovery at the expense of grade. However, tests carried out by McLeavy et al (2001) indicate a strong interaction between bowl speed and pinch valve open duration. Results showed that higher upgrading is attained at a high pinch valve open duration and low bowl speed. High recovery was attained at lower pinch valve open duration and high bowl speeds. Interaction between pinch valve open duration and feed rate was observed in the current study, such that as the feed rate was increased it was possible to operate at lower pinch valve open duration. There is however, a limiting pinch valve open duration below which no concentrate is recovered and an upper limit above which there is no upgrading. Below the lower limit, the open time is too short to permit upgraded material to exit the concentration ring via the valves whilst above the upper limit, particles exit the concentration ring without any upgrading. A comparison of the Falcon C performance (where the valves are open throughout the concentration process and a smooth bowl),
and the CVD performance beyond upper limit pinch valve open duration can be a good indicator of the contribution of bowl design to continuous centrifugal concentration. It also gives a measure of the contribution of differential settling as a concentration mechanism in the CVD.

Both pinch valve open duration and pinch valve closed duration depend on pneumatic accessories (air valves and piping) and the response varies from one machine to the other. Therefore, it is necessary to determine the operating ranges for these parameters prior to running a CVD machine and to follow a process optimization procedure to identify the best operating conditions.

2.2.6 Commercial CVD applications

Current commercial applications for the CVD include:

- Scavenging (sulphide, ferrochrome from slag)
- Impurity removal (iron oxide from talc)
- Primary recovery (tantalum, tin and chromite)

2.2.7 Recent CVD research

McLeavy (2005) used fractional factorial design experiments on quartz/magnetite synthetic ore to determine the main effects of four machine variables and four feed variables on recovery and grade. The crucial findings include ascertaining pinch valve timing, bowl speed and fluidization water velocity, as the main machine variables and showing that interaction of machine variables is significant. He also demonstrated that fluidization water flow rate has no significant effect on both grade and recovery when the CVD6 is operated between 7-10 gal/min, and thus it can be eliminated as a machine variable by operating within this range. He also proposed the use of the grade versus recovery upper boundary line (defined by the line joining the upper extreme points in the response domain) as a measure of optimum performance, provided the range of data adequately covers the design domain. The main challenge with this approach is the number of experiments required to cover the design domain given the interaction effect of the design variables.

The operational approach proposed by McLeavy (2005) consists of varying one variable at a time while maintaining other variables at their mid point. The results are used to generate concentrate grade versus recovery plots. The Operating Variable Performance (OVP) ratio (change in grade/change in recovery) is then used as the basis for CVD tuning. The weakness of this
approach is that it presupposes a linear relationship between variables and output, which does not hold because of variable interaction. A “one variable at a time” approach is potentially misleading when there are multiple complex interactions of variables (Altun et al., 2006; Montgomery & Runger, 2002). An improvement to this approach would be using Taguchi’s orthogonal arrays (Taguchi, 1987) instead of varying one variable at a time.

Klein et al (2010) tested hybrid flotation-gravity circuits on scavenger flotation tails at the Eskay Creek Mine. Figure 2.8 (a) shows the flowsheet of the tested application. By exploiting flotation performance dependence on particle size [i.e. between 10 and 100 microns as shown in Figure 2.8 (b)], the CVD is retrofitted so as to recover coarse middlings. They demonstrated that the CVD recovers coarse middlings shown by the circled region. The hybrid circuit has the potential benefit of increasing throughput while lowering grinding energy requirements by allowing coarser grinding. In addition, the preferred size distribution can be attained, which increases flotation recovery by reducing fines generation and capturing middlings by the CVD for further liberation.

![Figure 2.8: The hybrid CVD-flotation circuit tested by Klein et al (2010), showing integration of CVD technology to scavenge gold from tails (a) and a typical particle size distribution in a flotation plant showing flotation recovery dependence on particle size (b).](image)

### 2.2.8 Summary of CVD technology

The CVD is a relatively new technology whose physics of operation is still not fully understood; therefore no mechanistic or phenomenological models exist to describe the
concentration mechanism. Compared to other continuous concentrating technologies, the CVD is intermediate in complexity with regards to the number of operating variables. It has complex interacting variables rendering traditional optimization difficult. At present, there are no clear commissioning and performance improvement strategies: operators do not know whether they are operating the CVD “optimally” and they do not know how to tune the interacting variables so as to achieve the best performance. In addition, each CVD machine is unique, with unique operating parameter ranges due to variations in their pneumatic systems. For each new installation, there is need to determine the operating range of parameters and then tune the interacting variables to achieve maximum metallurgical performance. It is therefore necessary to develop a reliable methodology to efficiently tune the operating variables of the CVD and not just optimize a single CVD unit. This research intends to develop an approach for tuning operating variable levels in order to achieve optimal performance and provide understanding on separation mechanisms of the CVD.

2.3 Process optimization

Mineral extraction involves gangue rejection in order to produce a high-grade concentrate. Maximising concentrate grade can only be achieved at the expense of a reduction in recovery, since some of the valuable minerals will be rejected with gangue to achieve a higher grade. The operating line, which is the optimum grade versus recovery curve for a unit process, is therefore a trade off between maximising grade and recovery. The liberation limited grade versus recovery line obtainable from mineral liberation analysis shows the maximum attainable separation (perfect separation) of valuable minerals from gangue, only limited by the extent of liberation (Miller et al., 2009). Equipment inefficiencies, operating conditions and ore characteristics impose a limit to the actual attainable separation such that the operating curve is always lower than the liberation limited grade versus recovery curve. The objective of improving operational performance for the CVD and any other mineral extraction unit processes should involve identifying the optimum grade versus recovery curve and adjusting the operating conditions in order to run the process along the optimum curve.

Conventional approaches to mineral processing optimization involve preference-based methods that impose prior weighting on grade and recovery subject to financial utility functions. Optimization therefore yields only one solution instead of a set of points defining the operating curve. This approach depends on metal economics, such that every time metal prices change
significantly a new optimum has to be found. Given the competing relationship between grade and recovery, both a single objective function with several constraints and a weighted objective subject to metal prices constraints are limited in scope for generating an operating line. Pareto optimization allows for the grade versus recovery curve, which is a function of processing conditions, machine and ore variables, to be determined independent of metal economics. Then using metal economics, the optimum combination of concentrate grade (quality measurement) and recovery (quantity measurement) can be determined, thus marking where on the operating curve the process should be run.

Optimization is a broad term, but for purposes of this research it shall be defined as finding the best way to operate (Mular, 1974; Bacon, 1966; Goodwin et al., 2008). Optimization of CVD performance involves determining the operating line for the CVD. Both grade and recovery models have to be developed as functions of machine variables, such that the optimization solution will include the best grade versus recovery combinations and the corresponding machine variable levels. Figure 2.9 shows a schematic of the steps involved in process optimization. In the absence of mechanistic or phenomenological models, empirical models are developed from data obtained from exploration of the design space; otherwise exploration is attained by simulation. The models are then used to define the objective function for optimization.

![Figure 2.9: Schematic of process optimization.](image)

The first three steps are interdependent such that, although formulation of an objective function (based on fitted model) requires data to have been generated by exploration of the design
space, in order to decide on the suitable approach to explore the design space, knowledge of the model to be fitted is required, which depend on the number of independent variables and their ranges. The boundaries of the design region, which are a result of either physical or process limitations imposed on the variables, have to be determined first. For example, the CVD machines should not be operated above 90 g and the lower limit is set to 30 g. In practise however, it maybe found that due to other process factors, the machine cannot be operated above 80 g, this sets an upper boundary to the bowl speed for the particular application. Once the boundaries have been defined, the design space can be explored either by simulation or experimental tests. Statistical experimental design is efficient at exploring the design space using limited experimental runs.

Honaker & Das (2004) applied the steps in Figure 2.9 to optimize ultra fine coal cleaning using a CVD6. Although it is not clear how the variable levels were obtained to define the boundaries, once the boundaries were determined, Box Behnken design was used to explore the design space for four variables (bowl speed (BS), pinch valve open duration (PVO), pinch valve closed duration (PVC) and fluidisation water velocity) using 30 experimental runs. Least square regression was used to fit quadratic models to the experimental data. Quadratic models with second order interactions adequately predicted response for both recovery and product ash content. A non-linear optimization technique was used to optimize the two response variables, yielding a grade versus recovery relationship that was experimentally validated and compared to both washability and release analysis results. It is not clear how both objectives were optimized, but it appears simulation runs were conducted to generate the ultimate grade recovery relationship. The main challenge for their approach is how to simultaneously optimize the opposing objectives (recovery, and product ash content) without prior weighting of the objectives.

In this research, the Pareto genetic algorithm was used for simultaneous optimization because its reliance on a population allows it to retain a set of solutions that represents all the best trade-offs (Wiele and Michielssen, 1997), thereby avoiding the problem of having to formulate an algebraic expression to balance the competing goals. Mular & Herbst (1980) proposed a systematic approach for developing empirical models employed in this research, which include:

(1) Defining the process responses,
(2) Identifying the independent variables and specifying their ranges,
(3) Selecting appropriate form of mathematical model,
(4) Based on the selected model determining a suitable way to explore the design space,
(5) Adjusting the raw data to smooth it from error due to process fluctuations, sampling, instruments calibration and assaying then

(6) Fitting models on experimental data and performing adequacy tests. Once reliable models are determined, they can be used to formulate objective functions, which can then be optimized.

For the CVD the main machine variables are bowl speed and pinch valve open and closed duration. Preliminary studies conducted in this research showed that upgrade ratio is a better performance objective than concentrate grade for optimization purposes. Second order statistical experimental designs were used for collecting data and quadratic models with second order interactions adequately modelled response. Artificial Neural Network simulation was used to smooth out experimental data prior to fitting models.

2.4 The Pareto optimization approach

The CVD optimization problem reduces to a multi-objective optimization problem with two conflicting objectives and some constraints as shown in equations 2.10 and 2.11.

\[
F(x) = [F_1(x), F_2(x)]
\]

Max \( F(x) \) \hspace{1cm} 2.10

Subject to

\[
l \leq x_i \leq u
\]

where \( F(x) \) is a vector of objectives, \( F_1(x) \) representing concentrate grade/upgrade, and \( F_2(x) \) representing recovery. Since \( F(x) \) is a vector, and its components \( F_1(x) \) and \( F_2(x) \) (concentrate grade and recovery) are competing objectives, there is no unique solution to this problem but a set of Pareto optimum solutions.

The concept of Pareto optimality, also called non-inferiority/non dominated optimality, formulated by Vilfredo Pareto in 1896 constitutes the origin of multi-objective optimization. The Pareto optimum solution is a locus of tangent points of the objective functions or boundary of the design region. A non-inferior solution is one in which an improvement in one objective requires a degradation of another, which is the case in the concentrate grade-recovery relationship in mineral processing. The concept of dominance allows for comparison of solutions with multiple objectives and is used by many multi-objective algorithms to search for non-dominated solutions (Deb, 2001).
Dominance qualifies as an ordering relation because of its transitive nature. Given two solutions to a multi-objective optimization problem, one solution dominates if both conditions for dominance are satisfied. The conditions to be satisfied are:

(i) The solution should be no worse than the other for all objectives

(ii) The solution should be strictly better than the other in at least one of the objectives

Considering a problem with two objectives and five solutions as illustrated in Figure 2.10. Comparing solutions 1 to 5, solution 2 is better than 3 in both objectives and therefore dominates solution 3. Solution 5 is better in both objectives than solution 4 and therefore dominates solution 4. Comparing solution 1 and 2, it cannot be said which one is better than the other since solution 1 is better than 2 in grade, but worse in recovery. So solution 1 and 2 are considered non-dominated. Comparing solution 2 and 5, it cannot be said which of the solutions is better than the other, since solution 5 is better than solution 2 in recovery, but worse in grade. So, solution 2 and 5 are considered non-dominated with respect to each other.

![Figure 2.10: Demonstration of the Pareto optimization approach using a population of five solutions.](image)

Due to the transitive nature of dominance, since solution 2 is non-dominated by solution 1 and solution 5 is non-dominated by solution 2, therefore solution 5 is non-dominated by solution 1. A Pareto front is a set of such non-dominated solutions for an optimization problem. Solutions obtained in this research are Pareto Optimum curves based on simultaneously maximising both
upgrade ratio/grade and recovery subject to 3 CVD machine variables: (bowl speed (BS), pinch valve open duration (PVO), pinch valve closed duration (PVC). Fluidisation water velocity was kept constant.

2.5 Review of optimization techniques

Modern optimization approaches combine different methods in order to take advantage of their strengths. The following section reviews statistical experimental design, regression modeling, artificial neural networks and genetic algorithm optimization so as to find a way of combining them to develop an optimization approach for the CVD.

As illustrated in the previous section, optimization requires objective functions linking response to variables formulated by modeling. Models can either be theoretical, phenomenological or empirical. Depending on whether they are time dependent or not they can also be classified as dynamic or steady state. Compared to other model types, theoretical models are valid over a complete range of applications; however, they require a sound understanding of the process. Due to the complex interaction of ore variables and machine variables in mineral processing, models of this type are rare. The most popular mineral processing models are phenomenological models, developed from a mechanistic description of a process in conjunction with physically meaningful process parameters, determined from experiments rather than basic science (Wills, 1997; Burt, 1984). At present, the CVD separation mechanism is inadequately understood to formulate physically meaningful theoretical or phenomenological models. Thus, in this research, empirical steady state models are used for modeling CVD performance.

Parametric regression models have been used in the past to solve similar problems (Lind et al., 2006; Altun et al., 2006; Naik et al., 2005). These models have been used with response surface methods, which perhaps have the most published work in mineral processing optimization. Although these models are cheaper to generate and often lead to a better understanding of the process, they are application specific, subjective and depend on the expertise of the experimenter to effectively discriminate and select suitable and useful models from rival models (Donckels, 2009). Gravity concentration tests are also prone to sampling error and variation in feed grade, which can render optimization tests futile especially if there is marginal improvement in response to changes in operating variables.

Non-parametric regression models, with proven capability as universal function approximators, are often preferred for modeling complex processes with noisy experimental data
Campi et al. (1997; Hecht-Nielsen, 1990; White, 1989 and 1992). In particular, sigmoidal back-propagation neural networks (SBNN) have proven capabilities in modeling metallurgical and chemical systems satisfactorily without a priori knowledge of the system provided sufficient data is available (Van der Walt et al., 1993). This is attributed to their ability to self adjust the connection weights within the structure during training to adapt to example input-output patterns. Owing to the combined effect of their multi-layer structure and the non-linear activation function (sigmoidal), they can model relations that may be difficult to describe using conventional mathematical functions. A study that compared performance of regression models and ANN to predict the combustible value and flotation recovery of coal showed that artificial neural networks had superior prediction as measured by the coefficient of determination Jorjani (2009).

The use of ANN in output prediction and mineral processing optimization is a more recent development (Hao et al., 2004; Jensen et al., 2004; Labidi et al., 2007; Al-Thyabat, 2008 2009; Nakhaei, Mosavi, and Sam, 2013; Zhang, Wang, and Yu, 2007; Jorjani, Chelgani, and Mesroghli 2008; Jorjani et al., 2009; Panda et al., 2012). Earlier focus had mainly been on machine vision in flotation (Moolman et al., 1995; Bonifazi et al., 2001; Çilek, 2002) and in mineralogy and exploration (Huang and Wänstedt, 1998; Singh et al., 2001; Thompson, Fueten, and Bockus, 2001). The main challenge with non-parametric modeling like ANN, which may have limited its application in mineral processing modeling, is that the number of data points required to adequately model a process increases exponentially with increasing number of process variables (Walt et al., 1993). Less significant variables must therefore be removed prior to modeling. In this research, factorial experimental results obtained by McLeavy (2005) were used to identify the most significant control variables.

The high cost of assaying limits the number of data points that can be generated for modeling, thus compromising the quality of models. However, with better experimental design, it is possible to reduce the number of necessary data points required for ANN training. Past research in flotation demonstrate that strategic exploration of the design space can significantly reduce the number of necessary experimental runs required for ANN modeling. Al Thybats (2008) used thirty experimental runs to train and validate an ANN to simultaneously optimize phosphate flotation recovery and grade using three input variables. Jorjani (2008a) used 36 experimental runs to successfully train an ANN to predict the effect of five operational parameters on organic and inorganic sulphur removal from coal by sodium butoxide. Thus, using a strategic approach to
experimentally explore the design space can significantly reduce the number of experimental runs required to train a neural network, depending on the number of variables and the complexity of variable interactions. Agatonovic-Kustin et al (1998) argues that ANN are flexible with regards to the number and form of experimental data and thus informal designs could also be used to generate training data. The benefit of reducing the number of experimental runs, derived from systematic experimental designs (Kim et al., 2004; Takahara et al., 1997 and Erzurumlu et al., 2005) necessitates their application. This research proposes the use of circumscribed central composite design (CCCD) to strategically explore the design space and therefore reduce the number of tests required to train an artificial neural network with significant impact on both the cost and time requirement for experiments.

Artificial neural networks were selected in this research for modeling the noisy experimental data so as to identify the relationship between variables and outputs, in order to generate data for regression modeling. The choice of artificial neural network (ANN) modeling for the CVD is on the basis of the known complex variable interaction (McLeavy, 2005) and the ill-understood mechanism of concentration. The combination of these two would mean a large number of experimental runs are required to produce meaningful parametric regression models. However, response surface designs offer an efficient way of exploring the design space whilst minimizing the number of necessary experimental runs.

2.5.1 **Statistical design of experiments**

Experimental tests are expensive and time consuming and it is desirable to maximize the accuracy of information obtainable whilst minimising the number of necessary runs. The traditional “one variable at a time” approach to experimental design fails to locate the variable combination which yield maximum response when there are multiple interacting variables (Montgomery and Runger, 2002). This is because the approach fails to account for the synergistic effects (Altun et al., 2006). Statistical design of experiments, consisting of both factorial design (partial or full) and response surface design (second order design), offer a systematic way of exploring the design region respecting the epistasis of control variables and using minimum experimental runs. They are widely used in mineral processing optimization (Altun et al., 2006); Adinarayana & Ellaiah, 2002; Aslan, Cifci, & Yan, 2008; Aslan, 2008; Carley, Kamneva, & Reminga, 2004; Coulter & Subasinghe, 2005; Koppalkar, 2009; Tripathy & Rama Murthy, 2012).
Mineral processing applications are generally multi-variant, and less significant variables should be removed prior to experimental design in order to reduce the requisite experimental runs and produce a useful model. Partial factorial design can be used to identify important factors that affect the response by calculating the main effects of each variable. For the CVD, there are four significant machine variables, several ore variables, and two process variables (feed rate, pulp density). Only machine variables are considered in this research for testing the optimization approach as they can easily be manipulated by an operator in a processing plant. Quadratic models with interactions have been found to adequately model CVD applications (Honaker & Das, 2004).

Response surface designs are useful in fitting second order models using a minimum number of runs. These include 3-level Full Factorial, Central Composite, Box Behnken and Doehlet designs. For two variables, the efficiency of factorial design is comparable to central composite. However, when the number of factors is higher than two, full factorial design loses its efficiency in modeling multi variable quadratic functions because of the large impractical number of experiments required. Designs that require a smaller number of experiments such as the Doehlet, Box-Behnken and Central Composite designs are preferred. Figure 2.11 (a), (b) and (c) show design matrices for full factorial design, Box Behnken, and Central composite for three variables.

Although, Box Behnken design is more efficient and economical in selecting experimental points from three level factorial designs, it contains regions of poor prediction at the corners [Figure 2.11 (b)]. Central Composite Designs are more popular and have several varieties of designs, which provide flexibility when exploring diverse experimental regions. They can easily
be partitioned into two subsets, the first giving linear and two factor interaction and the second providing second order (curvature) estimates thus allowing for sequential experimentation (Myers, Khuri, & Carter, 1989), such that second order design experiments can just be added to the initial factorial experimental runs. They are also efficient at providing information on both experimental variable effects and experimental error using a minimum number of runs. Thus, Circumscribed central composite design was selected for design experiments in this research.

Central composite designs can be classified into inscribed, circumscribed and face centred depending on the positioning of the star points and factorial design points. Face centred central composite design allows for exclusion of unattainable operating conditions at the extreme of the design region. Face centered CCD, which is simpler, only requiring three levels of each variable, is preferable when unattainable operating conditions exist for only one of the extreme points. Rotatable designs (both inscribed and circumscribed) offer better prediction for quadratic effects, have less prediction error and better exploration of the design space, and are represented at five levels.

Central composite designs consist of three parts: a full or fractional factorial design with all the variables at their extreme levels, a star (axial) design obtained by changing one variable at a time by a factor $\alpha$, and central point repeat runs used for measuring experimental error. The most popular CCDs are rotatable designs, for which prediction error is only dependent on the distance from the origins and independent of orientation. Limits are imposed on the distance of axial points from the centre such that the value of $\alpha$ is given by:

$$\alpha = 2^{n/4}$$

where $\alpha$ is the normalised distance between the centre point and star points and $n$ is the number of variables. For the CVD, variables interactions may result in the optimum performance lying outside initially selected design region. For example, it was observed that by increasing the bowl speed, lower pinch valve open duration can be used, which otherwise would have yielded no concentrate at lower bowl speeds. Circumscribed central composite design (CCCD) was selected for CVD optimization because it allows for exploration beyond the initially selected design region to yield superior metallurgical performance.
2.5.2 Artificial Neural Networks (ANN) modeling and simulation

Artificial neural networks (ANNs) are non-parametric mathematical regression tools inspired by the biological nervous system. The human brain is estimated to contain $10^{11}$ neurons. Each biological neuron consists of dendrites, a cell body and an axon. Figure 2.12(a) is a schematic of a biological neuron showing the main features of interest. A membrane that has a negative electric potential at its resting state covers the cell. Communication with other neurons is via synapses, which are narrow gaps between dendrites. When cell body potential exceeds a threshold, the neuron fires (generates) a pulse, which travels through the axon, crosses the synapse, and enters the dendrites of neighbouring neurons. When a signal arrives at the synaptic membrane, a neurotransmitter proportional to the strength of the incoming signal is released from the vesicles. The neurotransmitter diffuses within the synaptic gap towards the post-synaptic membrane, and eventually into the dendrites of neighbouring neurons. The dendrites receive signals from other neurons and pass them over to the cell body, forcing it to generate a new electrical signal depending on the threshold of the neuron. The factors determining the strength of a signal that passes through a receiving neuron are intensity of the signals from each of the feeding neurons, their synaptic strengths, and the threshold of the receiving neuron. A neuron thus, acts like a simple micro-processing unit that receives and combines signals from other neurons and, depending on the strength of the overall signal, produces an output signal that may be transmitted to other neurons. Typically, a neuron has a large number of dendrites and synapses; hence, it can receive and transfer many signals simultaneously (Basheer & Hajmeer, 2000).

![Figure 2.12: A schematic of a biological neuron (a) and a single processing element artificial neural network (b) showing the main features.](image-url)
A typical artificial neural network model consists of several layers of processing elements. Figure 2.12 (b) shows a typical processing element, the $j^{th}$-processing element in an artificial neural network, which has $n$ inputs. The weighted values of $w_{ij}x_j$ are combined to form an internal activity level of $I_j$ analogous to the synaptic activity. The combined input is then passed through a transfer function $f$ (the soma activity) before going directly to an output path $Y_j$ that in turn may become the input to one or more processing elements. Axon and dendrites are analogous to connections and nodes, while synapses are analogous to connection weights in artificial neurons. According to Basheer & Hajmeer (2000) the following assumptions underlay the formation of ANNs, and thus, distinguish them from the biological neurons:

- Each node has only one output value, which is distributed to the other nodes via links.
- All inputs are given simultaneously and remain activated until the computation of the output is completed.
- The position on the node of the incoming connection is irrelevant

In addition, ANNs are homogeneous and often operate deterministically, whereas biological neurons are extremely heterogeneous and operate as a mixture of complex deterministic and stochastic processes. ANNs have few neurons and a lower interconnection density than biological neurons. However, in terms of functionality ANNs compare to biological networks.

The desirable characteristics of biological neurons mimicked by ANNs include nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and the ability to generalize. For ANN models, nonlinearity allows for better data fitting whilst robustness provides accurate prediction in the presence of uncertain data and measurement errors. Generalization enables application of a model to new data sets, high parallelism allows for fast processing and hardware failure-tolerance and adaptability enables the system to update its internal structure in response to changing environment.

### 2.5.2.1 Applications of ANN in mining and mineral processing

ANN applications include simulation, analysis, control, prediction, speech recognition, fault diagnosis, signal or image identification and optimization. ANN research in mining and mineral processing has focused on froth characterization in flotation (Bonifazi et al., 2000; Cilek, 2002 and Moolan et al., 1995) and in mineralogy and exploration studies centred on image

More recent work has seen an increase in application of ANN in output prediction and optimization of mineral processing operations: (Hao et al., 2003; Jensen et al., 2004; Labidi et al., 2007; Jorjani, 2008a; Jorjani, 2008b and Al-Thybatis, 2008). These studies focussed mainly on training networks and then using the trained networks for simulation to predict parameter settings yielding superior performance. The weaknesses of a simulation optimization approach, as applied in these studies, include the lack of analytical expressions for objective functions and constraints so that local curvature cannot be calculated. Because of the stochastic nature of the approach, complete enumeration of the design region cannot be guaranteed and optimization depends on whether the combination of parameters yielding optimum performance has been simulated. In addition, the approach does not guarantee simultaneous optimization of competing objectives (grade and recovery).

In the current research, ANN simulation was used to identify process trends from noisy experimental data, and provide more uniform data for use in parametric modeling. As a result of the complex interaction of predictor variables for the CVD, the resultant objective functions can have complex response surfaces. Although some applications may have simpler models, second order regression equations with interactions are likely to characterise recovery and or upgrade response to the predictor variables. Deterministic optimization methods fail when the objective function is multi-modal, but genetic algorithms are less prone to converging to a weak local optimum.

2.5.3 Optimization algorithms

This section will review some of the optimization algorithms and highlight the superiority of genetic algorithms for the CVD optimization problem. In most cases, the experimenter wishes to move from current operating conditions to the optimum region in the most efficient way by using the minimum number of experiments or minimum number of iterations. The choice of an optimization algorithm depends on the nature of the problem (objective function and constraints). The simplest expected model for the CVD is second order with interactions and it can be multi-modal as a result of variable interactions. An optimization technique able to avoid false minima/maxima is required.
Although there are many optimization algorithms, recent researches show the dominance of response surface methods (RSM) for modeling and optimization of mineral processing applications (Özgen et al., 2011; Aslan, Cifci, and Yan, 2008; Aslan and Fidan, 2008; Aslan and Ünal, 2009, 2011; Aslan, 2007, 2008a, 2008b; Celep et al., 2011; Tripathy and Murthy, 2012; Adinarayana and Ellaiah, 2002). It involves: (1) screening of variables of major effects; (2) selection and performing experimental designs in order to strategically explore the design space which normally involves second order designs (Box Behnken, Central composite designs and Doehlert designs); (3) model fitting and evaluation of the model fitness; (4) response surface analysis and optimization (Aslan, 2007; Bezerra et al., 2008). In order to perform displacement towards the optimum region, the method of steepest ascent is employed. This method fails when the function in question is either not differentiable or non-continuous. It also has difficulties when unknown disturbances cause severe changes in the measured response.

The Simplex method, developed by Nelder and Mead (1965) is another alternative approach, it has been successfully applied in grinding and flotation, (Mular, 1974). A starting simplex moves on the response surface by reflection into an adjacent simplex. It is forced to adjust to the local landscape, elongating up rising planes, changing directions on encountering a hill at an angle and contracting in the neighbourhood of an optimum. The Simplex method requires less computation time and offers solutions when functions are non differentiable. Its convergence speed has been found to increase with increasing range of the sensitive parameters (Scheidt et al., 2006). It however, can easily be entrapped in local minima and fail to reach the global optimum for complex response surfaces.

Another approach is the Rosenbrock direct search method, which calculates orthogonal directions coinciding initially with the coordinate directions, and then steps are taken in each direction from the starting point. At each step, the response is compared with the initial point. If an improvement is realised, the step size is increased by a factor of 3, otherwise it is reduced by a factor of 0.5. The procedure is continued until one failure and one success is recorded in each direction, then a new orthogonal direction is calculated. This approach has been successfully applied in flotation optimization (Woodburn et al., 1969).

A notable online optimization approach is Evolutionary Operations (EVOP), developed in the 1950s by Box, which effect process improvement without interfering with production. This is achieved by introducing small changes in the process variables during normal production. These
changes are not large enough to result in non-conforming product, but are significant enough to
determine the optimum process range. The philosophy behind the approach is that a process should be run so as to generate both product and information on how to improve the product. Application of EVOP in mineral processing has not been fully pursued as evidenced by the small amount of published work in that field. Applications of EVOP in mineral processing only focused on flotation optimization (Gould, 1967; Hamilton, 1967; Eggert, 1967) and there has been no further work since. However, the volume of successful applications in other fields still makes it a potential tool to be fully exploited in mining and mineral processing.

EVOP does not replace conventional optimization techniques but rather it complements them. The traditional experimental design and Taguchi methods seek to establish an optimum combination of the design factors and their proper levels. They are most suited for commissioning and troubleshooting whilst EVOP offers a continuous investigative routine for production processes. Challenges associated with the traditional optimization techniques include; cost, time, special manpower requirements and interruption of production. Box (1957) shows the optimization niche for EVOP and how it can solve the problems associated with scaling up. EVOP is best suited for optimizing full-scale plants once the initial operational approximation has been arrived at using traditional optimization techniques. It speeds up the location of the full-scale optimum operating conditions.

Recent developments in EVOP involve automation of the process (Holmes & Erhan, 2006; Holmes & Holmes, 2002) and development of Simplex Self Directing Evolutionary Operations (SSDEVOP), which are capable of responding swiftly to a shift in the optimum. An optimization approach that integrates the benefits of traditional approaches and evolutionary operations will be beneficial to mineral processing applications.

Other techniques include; Grid search method, which is laborious because of the large number of experimental runs and can be misleading in the presence of large process error. Indirect methods such as the Newton-Raphson Method rely on calculating derivatives using calculus. At a maximum, minimum, or point of inflection, the first derivative is zero. If the second derivative is zero then a point of inflection exists; if positive, then the point is a minimum; and if negative then the point is a maximum. These are relatively simple methods, which fail when the response is complex and non-linear, so they have limited applications in mineral processing optimization.
Taguchi’s method of maximizing the signal to noise ratio (MSNR) offers a competitive alternative to classical techniques when there are many predictor variables. Aslan (2008) used this approach to simultaneously optimize chromite grade and recovery by a Multi-gravity separator (MGS) by varying drum speed, tilt angle, shake amplitude, shake frequency, wash water flow rate and feed solids. He used orthogonal arrays for experimental designs and Taguchi quality loss function to maximize both grade and recovery simultaneously. This approach was a positive step towards using the already known relationship between (concentrate grade and recovery in mineral processing.

Unlike classical optimization algorithms based on mathematical procedures that suffer the set back of local entrainment, meta-heuristics can avoid local entrainment by accepting a “not so good” result as an improvement in the objective function and therefore proceeding in an optimum direction that mathematical procedures would have aborted. There are three categories of meta-heuristics: physically-based inspiration such as Simulated annealing; socially-based inspiration such as Tabu search; and biologically-based inspiration such as Ant colony, Artificial immune systems, Memetic algorithms, Particle swarm Optimization and Genetic algorithms (Ratanaphanyarat et al., 2009). Genetic algorithm was selected in this research due to its population based optimization approach.

Recent reported application of genetic algorithm optimization in mining and mineral processing has attempted to optimize coal preparation plants with the objective to maximize overall revenue by searching the best combination of overall yield and multiple-product quality constraints (Gupta et al., 2007). The optimization program generated grade versus recovery data using model equations for each circuit and then used the data to determine the optimal yield for maximum revenue. The fitness function used was a financial model, such that the best recovery or grade combination is selected on the basis of maximizing profit. Financial models are however subject to metal economics and other factors external to plant processes. It is desirable for any mineral processing unit operation to be able to determine the boundary/extreme limits of metallurgical performance. This is referred to as the operating line in this research. In order to obtain the operating line, the conflicting mineral processing performance objectives (grade and recovery) should be optimized simultaneously.

Since the CVD optimization problem has two objectives; maximizing concentrate grade (or upgrade ratio) and recovery subject to boundary constraints, it can be solved as a multi-
objective optimization problem. Various authors have formulated strategies to tackle such problems. Khuri & Conlon (1981) reviewed multi-objective optimization techniques and formulated a strategy that was successfully applied by Takahara et al (1997) to optimize two response parameters in pharmaceutical formulations using a distance function to reduce the multivariate to a univariant optimization problem achieved by minimizing the distance function. The limitation of this approach is that the formulation of the distance function is deterministic. Al-Thyabats (2008), used the method of super-positioning of response contours (Khuri et al., 1981) to determine the levels of four flotation variables to optimize both the grade and recovery of phosphate from Jordan with respect to three control variables (feed mean size, collector dosage and impeller speed). Optimization was achieved by dividing the parameter ranges into 100 equal intervals and then plotting superimposed graphs of ANN simulation results on recovery and grade against experimental number. This approach suffers the setback of other simulation optimization techniques, which do not guarantee optimization since it is highly depended on the efficiency in generating the intervals to explore the whole design space. The results can be misleading when parameter interactions are significant.

Genetic algorithms are a class of computational techniques inspired by the evolutionary principle of natural selection, often viewed as function optimizers. They have a broad range of applications. Unlike classical optimization methods, genetic algorithms do not necessarily operate directly on the design parameters; instead, they use a population-based search to identify candidate solutions that maximize the objective function subject to constraints. By their stochastic nature, genetic algorithms can optimize multi-modal, non-linear functions with multi interacting variables.

Pareto genetic algorithms offer a superior solution to multi-objective problems by avoiding a priori formulation of a function to balance the competing goals. They give a set of non-dominated solutions instead of a single optimum point (Deb, et al., 2000). Such a solution is preferable in mineral processing where there is need to adjust the grade versus recovery operating point with changes in metal prices and other externalities. Whilst arriving at a single ‘optimum point’ in mineral processing requires economic considerations, determining the optimum grade versus recovery curve (regarded as optimization in the current work) is a purely metallurgical problem, independent of higher-level decision-making. The optimum grade recovery curve for a unit process can therefore be defined and the parameter combinations yielding that curve determined through purely mineral processing optimization, leaving the choice of combination of
grade and recovery to economic variables. The population-based approach used in genetic algorithms allows for such an optimization problem to be effectively solved.

**2.5.4 The hybrid optimization technique**

Several authors have demonstrated the use of a combination of ANN and statistical experimental design to solve optimization problems in ill-defined processes with multiple control variables and/or complex interactions (Kim et al., 2004; Agatonovic et al., 1998; Erzurumlu et al., 2005 and Jorjani et al., 2008). Kim et al., 2004 successfully used the strategy to predict plasma-etching rate of aluminum thin films with six control variables of which some had interactive effects. Two level experimental designs were used to generate training data and the trained network used to predict and generate 3-D response surfaces. Takahara et al (1997) used the same approach to optimize pharmaceutical formulations. Common with all these authors is the application of neural networks to predict response. Unlike regression models, which depend on predetermined regression polynomials, the ANN models are probability based and are able to determine trends even in noisy data, thereby yielding superior prediction models to regression.

The choice of statistical experimental design is based on past researches, which demonstrate its effectiveness in generating systematic parameter combinations to train neural networks (Kim et al., 2004; Takahara et al., 1997; Erzurumlu et al., 2005). Despite the flexibility of ANNs with regards to the number and form of experimental data (Agatonovic-Kustin et al., 1998), systematic experimental design is advantageous when dealing with control variables, which have complex interactions where effective exploration of the design space would otherwise require lots of tests.

This research pursues potential benefits, which can be derived from integrating ANN, statistical experimental design, and genetic algorithm in optimizing CVD performance.

**2.6 Summary**

From the reviewed literature, the concentration mechanism of the CVD is not yet fully understood, there is still need to clarify the contribution of fluidization and how the centrifugal force influences separation of different mineral species. It is not yet established whether mineral upgrading occurs in the concentrate ring, such that the contribution of pinch valve timing to mineral upgrading and recovery is still to be studied. As a result, there are no mechanistic models developed to date for the CVD and there are no adequate data to formulate such models.
Therefore, empirical models were used to model CVD application for performance optimization in the current research. Response surface designs, regression modeling, artificial neural networks and genetic algorithms have been successfully used for optimization in mineral processing. Thus, application of these techniques individually is not new to mineral processing but integration of all four to produce an optimization strategy as described in this research work is new and has potential to yield superior optimization results.
Chapter 3: A novel bench scale procedure to predict CVD performance

3.1 Introduction

Evaluation of ore amenability to concentration precedes application of the technology in mineral processing. Existence of a reliable technique capable of determining maximum recoverability is crucial for benchmarking process performance. Gravity recoverable gold (GRG) refers to gravity recovery of free gold, and is defined as gold in particles whose gold content is high enough to be selectively recovered by gravity methods at relatively low mass yields, typically 0.1 % (Clarke, 2005). By definition, it does not account for gold associated with sulphides which, although recoverable by gravity, is typically in small quantities and require high mass yield. There is therefore a need to find a measure for gravity amenability for high mass yield applications typical for continuous centrifugal concentration, characteristic of heavy minerals, and gold associated with sulphides.

To date there are no laboratory scale continuous centrifugal concentrators such that testing application would require the use of pilot machines and large sample quantities. The existing laboratory procedures have limitation in predicting continuous centrifugal concentration and therefore need to be improved. The objectives for this chapter include: investigating suitability of the MD3 machine for predicting CVD application, assessing suitability of current laboratory procedures for predicting CVD performance, developing a new laboratory procedure for predicting potential CVD performance and evaluating the developed procedure through testing on real ore.

According to the guidelines for procedures used to predict fundamental response by Pratten (1989), results from float-sink analysis are not suitable for characterising enhanced gravity concentration due to the difference in the mechanism of separation. The laboratory scale Knelson Concentrator (MD3) is better suited for characterising gravity recovery by centrifugal concentrators. Its application in predicting gravity concentration is widely accepted as evidenced by its application in determining gravity recoverable gold (Banisi, Laplante and Marois, 1991; Laplante and Shu 1992; Woodcock and Laplante, 1993; Laplante, Woodcock, and Huang 2000). Spillers (1992) and Banisi (1991) showed the MD3 was capable of recovering up to 95% of amalgamation recoverable gold below 400 µm from low-density gangue. Past researchers (Clarke,
2005; Huang, 1996; Woodcock, 1994, Banisi, 1990; Putz, 1994) have confirmed the reliability of the laboratory Knelson concentrator for predicting GRG content.

The MD3 is designed to recover very dense minerals from lighter ones. According to Laplante (2000) there are three phases of the Knelson recovery cycle; initially, gangue and dense minerals alike indiscriminately fill bulk of the concentrate rings capacity. The second phase results in the formation of a secondary layer attributed to gold bearing sulphides and the third phase, constitutes very high density particles mainly gold and tramp iron (Clarke, 2005). The conical bowl design with wedge profile reduces variation in bowl speed as particles travel up the bowl (Banisi, 1990). Lighter particles at the surface of the concentrate bed are continuously replaced by heavier ones due to motion within the bed (Banisi 1990, Clarke 2005) and the Bagnold effect allows for fine dense particles to trickle down the bed due to dispersive forces induced by bowl motion favouring recovery of fine dense particles (Clarke, 2005). However, very fine (below 25 microns), flakey and rod like gold particles which report to the cyclone overflow due to over grinding are poorly recovered by the MD3 such that a GRG measurement of any processing stream after grinding and classification is likely to yield an atypical grade versus recovery relationship. Higher bowl speed is favourable for fines recovery and high fluidization is desirable for coarse particles and higher density gangue (Ounpuu, 1992).

The concentration mechanism for a laboratory Knelson Concentrator is fundamentally similar to that of the CVD in that in both machines particles are separated in a fluidised bowl rotating at high centrifugal force. The main mechanism of separation in both machines is differential particle sedimentation in a centrifugal force field. The main design difference is that the CVD has pinch valves that can discharge the concentrate without need to stop the machine, whilst the MD3 has to be stopped in order to remove the concentrate accumulated in the rings. When the MD3 is operated at high mass yield, it approaches CVD performance. To date, there are two laboratory procedures, the Multi pass test (Ghaffari, 2005) and the Gravity amenability test (GAT), which use the MD3 to predict CVD performance. However, both laboratory techniques fail to adequately characterize samples for high mass yield applications characteristic of the CVD. Typical continuous gravity concentrator applications are high mass yield and usually open circuit. There is need to adjust the MD3 feed mass in order to achieve a mass yield in the range of the CVD.
The GRG test developed in the early 1990s (Woodcock & Laplante, 1993) was designed to characterize gravity recoverable gold in the grinding circuit, (Laplante and Dunne, 2002) and has evolved to be the industry standard for assessing gravity amenability of gold ores (Huang and Koppalkar, 2007). Since over 95% of GRG reports to cyclone underflow (Laplante, Lui and Cauchon, 1998; Banisi, Laplante and Marois, 1991; Laplante and Shu, 1992; Woodcock, 1994), gold recovery in the grinding circuit is closely associated with both grinding and classification efficiency. The GRG test procedure was designed to capture gold liberation related information. The caveat is distinguishing material characteristics and the effect of machine efficiency when using one particular concentration device to determine gravity amenability (Kelly and Spottiswood, 1982). Subasinghe (2007, 2008, 2012) argues that GRG is a machine dependent characteristic, which is a function of feed size and the force acting on the particles, and is therefore different for the MD3 and industrial units. He advocated for the use of a partition curve determined by subjecting fully liberated (synthetic) ore to machine separation, which is a function of fluidization water velocity. The GRG procedure is a material characterization test that provides information on the degree of liberation of the ore, the influence of breakage characteristics on liberation, and amenability of the ore to centrifugal gravity concentration (Koppalkar, 2009). It offers the upper limit of gravity recovery performance for an ore (Clarke, 2005). However, the cost, labour and weight (40-100 kg) requirement for the standard GRG test limits its application for routine testing. A simplified GRG test using less material (20 kg) and involving a comminution step (crushing and grinding) targeting 80% passing 75 µm, followed by a single pass in a MD3 was proposed and tested by Clarke (2005). The simplified test under-predicted the GRG in the samples and was therefore not suitable for characterizing ore amenability. Instead, it provided a better measure of expected plant performance, since the industrial units are known to recover about 66% of the GRG predicted by the standard test. The simplified GRG test demonstrates that a single pass test with less starting weight can be used to predict plant performance provided an adequate representative sample is used.

Xiao (2008) developed a laboratory method to characterize gravity recoverable platinum group minerals (GRPGM) which he defined as the portion of platinum group minerals in an ore stream that can be recovered by gravity at a low mass yield (< 1%). This includes fully and partly liberated PGMs recoverable to the concentrate whilst excluding fine fully liberated PGMs unrecovered on account of size, as well as PGMs in solid solution in carriers such as copper or
nickel sulphides. Continuous centrifugal concentrators target recovery of heavy minerals instead, and above 50% of commercial CVD applications are in gold associated with sulphides with typical mass yields above 5%, implying that none of the available laboratory procedures is designed to best mimic such applications. In addition, as the CVD is mainly used in scavenging applications, the feed to the CVD is already ground and thus the size liberation data obtainable for the conventional GRG test can only be obtained from recovery by size instead of stage wise comminution. Xiao (2008) demonstrated that the current standard procedures could be modified in order to better predict gravity recovery for other applications.

A novel procedure code-named Gravity Release Analysis (GRA) was developed in this thesis for predicting CVD application. According to Pratten (1989), for a procedure to be satisfactory for characterizing fundamental response, the following should be taken into consideration: “Results should describe a recovery versus grade locus and not just a single point for meaningful comparison of performance. The recovery versus grade locus must represent the limit of gravity recovery. The procedure should be based on the same separation mechanism i.e. an enhanced gravity based laboratory procedure should be used for assessing enhanced gravity separation, rather than using the widely acceptable sink-float analysis. Results of the procedure should depend on the ore and not on machine parameters. The procedure should be applied to the entire feed and not just a limited size fraction. The procedure should be simple, error-free and be able to be performed routinely in the laboratory in an operator-independent manner. The procedure should be repeatable and reproducible.”

The GRA procedure was developed from flotation release analysis procedure (Dell, 1953), which is one of the standard methods of testing flotation kinetics (Dell, 1972). This chapter introduces and assesses the suitability of the GRA procedure for predicting CVD application by determining the maximum release of gold bearing sulphides (Gravity recoverable gold bearing sulphides) from a representative small (5 kg) sample. The procedure exploits treatment of small masses by the MD3, which enables substantial recovery of gold bearing sulphides (Woodcock, 1994). By providing a measure of maximum gravity recoverable gold bearing sulphides, the procedure provides a basis for bench making operating CVDs. In addition, a quantitative measure of gravity amenability for different metal species in an ore is introduced.
3.2 Materials and methodology

Tests were conducted on silica/magnetite synthetic ore and real ore. The real ore was obtained from a flotation rougher tailings stream of an operating mine treating an epithermal gold ore and from Myra Falls flotation tails, zinc concentrate and copper rougher tailings streams. For the synthetic ore, sized silica from Lane Mountain (LM # 20-30 and LM # 70) was blended in the ratio 1:3 and mixed with sized pure magnetite to constitute a 5% magnetite ore.

To characterise the real ores, 100g representative samples were riffled from samples obtained during pilot and plant trials at the epithermal gold ore mine and Myra Falls, and analysed using X-ray diffraction (XRD) at the Earth and Ocean Science University of British Columbia laboratory to determine the mineral occurrence. The Rietveld Topas 4.2 program was used for refining the X-ray powder-diffraction data. Scanning electron microscopy (SEM) was used for identifying mineral association for Myra Falls ore. Scanning Electron Microscopy (SEM) analysis was performed to identify the gold species recovered by the CVD. To ensure that the SEM sample will contain observables gold particles, a 5 kg CVD concentrate was collected during CVD6 pilot testing of the cyclone underflow at Myra Falls. By combining the Gravity Release Analysis and panning, as in the Multi pass test Ghaffari (2004), the CVD concentrate was further upgraded to produce a heavy fraction product mineralogical analysis. The panning concentrates were combined into the final gravity concentrate and used to prepare polished samples for SEM analysis. SEM with Energy Dispersive X-ray Spectroscopy (EDX) for elemental analysis was done at the UBC Materials Science laboratory using a Hitachi S3000N VP-SEM with EDX.

Figure 3.1 shows an MD3 used for tests in this chapter. Representative samples were riffled, weighed and poured into a feed hoper for feeding the MD3. The feed rate was measured by timing the feed into a bucket prior to testing. Preliminary tests showed that pulp density had no significant effect on MD3 performance. Unless specified, the parameters used for the MD3 tests in this research are shown in Table 3.1.
Figure 3.1: Laboratory Knelson Concentrator (MD3) picture and schematic representation of the concentration in the bowl.

Table 3.1: Test conditions for MD3 tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centrifugal field</td>
<td>60g</td>
</tr>
<tr>
<td>Fluidisation flow rate</td>
<td>3.5 gal/min</td>
</tr>
<tr>
<td>Solids Feed rate</td>
<td>0.5 kg/min</td>
</tr>
</tbody>
</table>

3.3 The effect of mass yield on laboratory Knelson concentrator performance

A single pass variable mass yield procedure, shown schematically in Figure 3.2, was developed and used to assess the effect of mass yield on MD3 performance. The main motivation in developing this procedure was to design a test procedure which best simulates a typical CVD application, where ore passes only once through the concentrator (open circuit), and capable of handling high mass yield.
Synthetic quartz/magnetite ore was used for the test program. Sized magnetite and silica was used to constitute 5% magnetite. Magnetite size distribution was confirmed by sieve analysis. The magnetite used in the test was prepared by running it in a Davis tube to clean it from non-magnetic materials. Samples weighing 5, 2, 1 and 0.5 kg were prepared and used in the tests. Each sample was run in the MD3 once according to the procedure in Figure 3.2. Both tailings and concentrate were assayed for magnetite content using the Davis tube and the results were used for metallurgical balance.

Real ore samples collected from flotation zinc concentrate and tailings streams at Myra Falls mine during CVD pilot and full-scale tests were subjected to the same test conditions in order to assess the effect of mass yield on MD3 performance. The samples were riffled into: one 2 kg sample, one 1kg sample, two 500 g samples and two 250 g samples. Each sub sample was run in the MD3 using the schedule shown in Figure 3.2. The concentrates were dried, weighed, pulverized and assayed to extinction for gold. The tailings were dried, weighed, rifle split to obtain representative samples, pulverized and assayed for gold. All assays were done at the International Plasma Laboratory (IPL) in Richmond, British Columbia.
Figure 3.3 (a) shows results of magnetite recovery versus mass yield, showing how recovery increases by varying the starting mass for a bench-scale test for different particle size. The coarser the particle sizes the higher the recovery. Figure 3.3b shows variation of magnetite recovery and upgrade ratio with mass yield. The synthetic ore results (a) and (b) show that increasing mass yield generally increases magnetite recovery and the magnitude of recovery depends on particle size. At low mass yield (typical of batch applications), particle size had no significant effect on recovery. This is attributable to the balance between heavy particle migrations into the concentrate bed, and bed erosion by the flowing film. A limit is imposed by the bowl speed on the bed depth at which continuous replacement of lighter particles by heavier ones occur, thus limiting the quantity of heavies retained in the concentrate ring. Beyond this limit a dynamic equilibrium is established such that although there is still particle transfer between the flowing film and concentrate bed, it is balanced by heavies lost due to bed erosion. Stratification of the concentrate bed which makes this assertion viable was demonstrated by Huang (1996). At higher mass yield, settling rate has the dominant effect, such that the larger particles are preferentially recovered.

Figures 3.3 shows the effect of increasing mass yield on MD3 performance. Both the recovery and upgrade ratio level off beyond a mass yield of 10%. Figure 3.3 (a) shows that the effect of particle size on recovery is not significant at low mass yield; therefore CVD applications (high mass yield) are more sensitive to particle size than batch. A trade off has to be established between the recovery benefit obtained at high mass yield and the increasing difficulty of obtaining a representative sample, when dealing with small feed samples. A mass yield of 10% was considered suitable for designing the rougher stage for any laboratory scale procedure based on the results. Upgrade ratio decreases with increasing mass yield as it follows the same trend as concentrate grade, but it is less sensitive to variation in feed grade.
Figure 3.3: The effect of increasing mass yield on MD3 performance showing (a) Magnetite recovery by particle size as mass and variation of recovery and upgrade ratio with mass yield for (b) synthetic ore, (c) Myra Falls zinc concentrate, and (d) Myra Falls flotation tails.

Increasing mass yield increases recovery for the bench scale tests, therefore a test that can represent CVD applications has to incorporate variation in the starting mass. The GAT procedure is not capable of predicting the high mass yields characteristic of CVD applications since the starting mass is fixed at 5 kg. Although higher mass yields are obtainable by reducing the starting mass for the GAT test, for gold samples it becomes increasingly difficult to obtain a representative sample with lower masses.
These results informed the design of the rougher stage for the GRA procedure. Lowering the starting weight increases the mass yield. The target mass yield for the rougher stage is when upgrade ratio tends to flatten out (be constant) as recovery continues to increase with increasing mass yield. Thus GRA rougher stages should be run at high mass yield (small feed mass to the MD3). There is a limit to decreasing the feed weight. As the feed is split into smaller fractions it becomes increasing difficult to get a representative sub-sample, therefore compromising the repeatability of the test results. Therefore, 1kg samples were considered appropriate for the GRA rougher stage tests.

3.4 Assessment of current gravity amenability testing procedures

In order to assess the adequacy of current procedures for predicting CVD application, tests were conducted on Myra Falls copper rougher tails. The Multi pass test shown schematically in Figure 3.4 and GAT procedure in Figure 3.5 were assessed. Two 5 kg samples collected from the Myra Falls copper rougher tails stream during CVD6 pilot scale testing, were used for gravity amenability testing and the results were compared to CVD6 performance.

![Diagram](Figure 3.4: The Multi pass test (Ghaffari, 2005).)
The samples were run in a MD3 according to the procedures provided in Figures 3.4 and 3.5. A bowl speed equivalent to a centrifugal force field of 60 g and fluidization water velocity of 3.5 gal/min were used for all tests. The concentrates were dried, weighed, pulverized and assayed to extinction for gold. Representative samples of the tailings were obtained by riffle splitting after drying, pulverizing and assaying for gold. All assays were done at the International Plasma Laboratory (IPL) in Richmond, British Columbia.

The results obtained from the Multi pass test and GAT test were plotted to generate cumulative recovery versus cumulative grade curves, which were compared to the CVD operating line obtained through pilot scale testing and optimization. Figure 3.6 shows the results.
Results show that both bench scale tests do not cover the broader feasible mass yield range typical of CVD applications. The CVD line exhibited inhibited gravity recovery at high mass yield, which was predictable by the GAT procedure. The un-recoverable gold can either be attributed to un-liberated fine gold associated with sulphides and gangue or gold rendered non-recoverable by over grinding. Although the GAT procedure covers a wider recovery range, the Multi pass test better predicted CVD application. Both approaches do not adequately cover the complete CVD mass yield range. An impractical number of repeats would be necessary to cover the high mass yield end of the CVD. Although a higher concentrate grade at the same mass yield would have been expected for the Multi pass test, the lower grades obtained for these tests indicates that some of the gold gets deported to the pan tails due to poor panning skills. Thus, the approach is highly dependent on operator skills and hence unsuitable for characterizing fundamental response Pratten (1989).

The crucial observations for these tests were that a smaller sized sample (5 kg) was adequate to predict CVD application within the mass yield range covered. The bench scale test results overestimate CVD performance and therefore can function as the upper limit for CVD performance. The GAT test predicts way above CVD performance and the Multi pass test, which has cleaning stages, better predicts CVD performance at low mass yield.
3.5 The Gravity Release Analysis (GRA) procedure

Gravity recovery by centrifugal concentration is a probabilistic process dependent on several factors including specific density, degree of liberation, particle morphology, particle size and machine parameters. Like floatability, gravity amenability is not an intrinsic property. The best case of centrifugal separation is what is achievable as separation stages are increased. Similar to flotation release analysis, the objective of the GRA procedure is to separate ground ore into fractions by centrifugal concentration to determine the maximum release of gravity recoverable species. Traditionally, this has been done using sink-and-float analysis in gravity separation. According to Pratten (1989), a laboratory procedure to characterise a fundamental response should be based on the same separation mechanism. Thus if the ore is to be concentrated by heavy media separation then the sink-and-float approach will be appropriate, but for centrifugal concentration application, the laboratory procedure should also be based on centrifugal concentration. The other limitations of the sink-and-float analysis include its inability to handle fines, the toxicity of heavy liquids used, and the lack of higher specific gravity heavy liquids suitable for mineral separations. The Magstream that uses heavy inorganic (non-toxic) liquids (Ferrofluids) in a combined centrifugal and magnetic field is an improvement of the conventional approach, but it also fails when testing fines.

More recent laboratory procedures developed to assess ore amenability to centrifugal concentration use laboratory centrifugal concentrators especially the Knelson MD3 (Banisi, Laplante and Marois, 1991; Laplante and Shu 1992; Woodcock and Laplante, 1993; Laplante, Woodcock and Huang, 2000; Xiao, 2008, Clarke, 2005; Ghaffari, 2005). As shown in the introduction to this chapter, the main difference between the MD3 and the CVD is the mechanism by which concentrates are discharged. CVD machines have air actuated pinch valves, which open and close to allow concentrate discharge, whilst for the MD3 has to be stopped in order to remove concentrates that accumulates in the rings. Therefore the MD3 is well suited for assessing CVD applications provided the difference in mass yield is accounted for.

In order to improve on the deficiencies of existing procedures, the Gravity Release Analysis procedure was designed to account for high mass yield applications. Also, the GRA procedure has cleaning stages that are less dependent on operator skills for separation, which is usually by flotation panning. This procedure is not meant to replace mineralogical liberation tests, but rather to give an indication of how much metal or mineral of value can be recovered by a
continuous centrifugal concentrator in a mineral processing circuit. The procedure was specifically
designed for determining applicability of CVD technology to recover gold associated with
sulphides in a processing stream using small sized samples but can be applied to any centrifugal
concentration application.

3.5.1 The Gravity Release Analysis experimental procedure

Figure 3.7 The Gravity release procedure in consists of a series of rougher-scavenger-
cleaner gravity tests using the MD3. The feed to the GRA test is based on sampling theory, and a 5
kg representative sample of the processing stream was considered adequate. The 5 kg sample is
rifle split into 1 kg sub-samples. The size of sub sample used in the GRA test is based on mass
yield test results (Figure 3.2), which demonstrate the recovery advantage obtained by using small
feed samples. The objective of the rougher and scavenger stages of the procedure is to recover all
gravity recoverable gold, whether liberated or un-liberated in sulphides or gangue.

For the MD3, increasing bowl speed favours recovery and leads to dilution of concentrates
by lower density species. It also favours recovery of fine particles. Increasing fluidisation flow rate
favours concentrate grade, with rejection of fine heavy particles, thus compromising the recovery.
Since recovery and grade are dependent on mass yield, by varying the MD3 feed mass and
therefore mass yield either grade or recovery can be maximised without adjusting bowl speed and
fluidisation flow rate. The lower the mass yield (high feed mass), the higher the concentrate grade
and the higher the mass yield (low feed mass) the higher the recovery. For the samples tested, a
mass yield of 10% was considered suitable as above it both recovery and upgrade ratio started to
flatten.

Each sub sample is run through the MD3 twice, collecting the concentrate after each run to
constitute 200 g of rougher concentrate. These concentrates are then combined for each sub sample
to constitute 1 kg rougher concentrate sample, which is then run 5 times into the MD3 collecting
concentrate at each run. The concentrates and a sample of the final tailings are assayed for the
target elements. For consistency, all tests were conducted at the same testing conditions shown in
Table 3.1.
3.5.2 Construction of gravity release curve

The results of the experimental procedure are in the form of weight and metal grade. The Gravity Release Analysis curve is generated in a similar way as the flotation release analysis curve by plotting the cumulative percentage recovery of metal as the ordinate, with the cumulative weight of concentrate per 100 units of metal as the abscissa. The ‘grade-gradient plot’, a plot of cumulative metal recovered versus ‘unit weight’, is the preferred way of representing release analysis data (Dell et al., 1972) as it allows for easy computation of the grade by computing the gradient. The construction is such that a vector represents a sample of ore with the horizontal length proportional to sample weight and the vertical length proportional to weight of metal contained in the sample such that the gradient of the vector is proportional to the grade of the sample. The release curve results from joining vectors of each fraction of the release analysis test (Dell et al., 1972).

3.6 Gravity Release Analysis for Myra Falls zinc flotation tails

To assess applicability of the GRA procedure in determining gravity amenability, the procedure was tested on Myra Falls zinc flotation tails. Since sulphide minerals are easier to assay
than gold, in order to assess gravity release of gold bearing sulphides, it is desirable to identify indicator sulphide minerals for gold.

A 100g representative sample of the flotation tailings was riffled and analysed using X-ray diffraction (XRD) to determine the mineral occurrence. The Rietveld Topas 4.2 program was used for refining the X-ray powder-diffraction data. Table 3.2 shows the results of relative amounts of crystalline phases normalized to 100 %.

Table 3.2: Rietveld analysis results.

<table>
<thead>
<tr>
<th>Mineral</th>
<th>Ideal Formula</th>
<th>% Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quartz</td>
<td>SiO₂</td>
<td>41.5</td>
</tr>
<tr>
<td>Clinohlore</td>
<td>(Mg₃Fe²⁺₅Al(Si₃Al)O₁₀(OH)₈</td>
<td>2.5</td>
</tr>
<tr>
<td>Muscovite</td>
<td>KAl₂(AlSi₃O₁₀)(OH)₂</td>
<td>22.7</td>
</tr>
<tr>
<td>Gypsum</td>
<td>CaSO₄·2H₂O</td>
<td>0.7</td>
</tr>
<tr>
<td>K-Feldspar</td>
<td>KAlSi₃O₈</td>
<td>1.7</td>
</tr>
<tr>
<td>Plagioclase</td>
<td>NaAlSi₃O₈ – CaAl₂Si₂O₈</td>
<td>1.8</td>
</tr>
<tr>
<td>Calcite</td>
<td>CaCO₃</td>
<td>1.9</td>
</tr>
<tr>
<td>Ankerite – Dolomite</td>
<td>Ca(Fe²⁺,Mg,Mn)(CO₃)₁₂ – CaMg (CO₃)₂</td>
<td>0.6</td>
</tr>
<tr>
<td>Pyrite</td>
<td>FeS₂</td>
<td>23.5</td>
</tr>
<tr>
<td>Sphalerite</td>
<td>(Zn, Fe) S</td>
<td>0.7</td>
</tr>
<tr>
<td>Barite</td>
<td>BaSO₄</td>
<td>2.3</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>100.0</td>
</tr>
</tbody>
</table>

The results show that pyrite is the main host mineral for iron. And therefore, iron assays are a good indicator for pyrite. Iron recovery can be used as indicator for base metal sulphides recovery and thus an indicator for gold recovery. However, the presence of clinohlore (2.5 %), which is a low specific density mineral with 11 % Fe, implies that the tailings iron grade may not be a measure of loss of the higher specific gravity sulphides, but instead can account for the iron deported in the lighter minerals. The following section presents the Gravity Release Analysis results for iron as an indicator of gold bearing sulphides and compares results with gold.

3.6.1 Iron gravity release results

The iron assays were measured using an XRF at Myra Falls. The Gravity Release Analysis results for iron are shown in Table 3.3. Figure 3.8 is the gravity release curve for iron showing a plot of cumulative recovery against the cumulative unit weight. From the release curve, it can be found that the iron feed grade is 9.6 % and it can also be calculated that a concentrate grade of 20.8 % iron can be obtained at a recovery of 29 % and a mass yield of (160/1038) % = 15.4 %.
Figure 3.8: The gravity release curve for iron, the dashed lines are the vectors whose gradient is a measure of grade.

The release curve can be used to determine the maximum attainable grade at a given recovery and mass yield. The shape of the release curve shows that iron and therefore pyrite exhibit inhibited gravity recovery, which is expected due to the relatively low specific density compared to gold.
Table 3.3: Gravity Release Analysis results for iron.

<table>
<thead>
<tr>
<th>Product</th>
<th>Mass yield (%)</th>
<th>Fe Grade (%)</th>
<th>Recovery (%)</th>
<th>Cumulative Recovery (%)</th>
<th>Cumulative Grade (%)</th>
<th>Upgrade ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Con # 1</td>
<td>1.8</td>
<td>25.0</td>
<td>4.7</td>
<td>4.7</td>
<td>25.0</td>
<td>2.6</td>
</tr>
<tr>
<td>Con # 2</td>
<td>1.6</td>
<td>24.4</td>
<td>3.9</td>
<td>8.6</td>
<td>24.7</td>
<td>2.6</td>
</tr>
<tr>
<td>Con # 3</td>
<td>1.7</td>
<td>22.2</td>
<td>3.9</td>
<td>12.5</td>
<td>23.9</td>
<td>2.5</td>
</tr>
<tr>
<td>Con # 4</td>
<td>1.6</td>
<td>19.5</td>
<td>3.3</td>
<td>15.8</td>
<td>22.8</td>
<td>2.4</td>
</tr>
<tr>
<td>Cleaner Tail</td>
<td>6.9</td>
<td>17.3</td>
<td>12.4</td>
<td>28.2</td>
<td>20.0</td>
<td>2.1</td>
</tr>
<tr>
<td>Tails</td>
<td>86.4</td>
<td>8.0</td>
<td>71.8</td>
<td>100</td>
<td>9.6</td>
<td>1.0</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>9.6</td>
<td>100</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3.9 (a) shows the effect of increasing mass yield on iron grade and recovery for flotation tailings at Myra Falls. Recovery increases with mass yield while grade decreases as expected. A plot of grade and upgrade ratio versus recovery (b) shows that upgrade ratio tracks the concentrate grade well when the variation in feed grade is minimal. Upgrade ratio is thus a preferable performance measure for purposes of optimization. Figure 3.9(c) is a comparison of upgrade versus recovery plots for the GRA and the CVD6 in order to assess the capability of the GRA procedure to predict CVD application. The CVD6 results were obtained from pilot scale optimization tests conducted onsite.
The CVD results track GRA results well such that, within margins of error, the GRA procedure provides a reasonable estimate of CVD performance for iron recovery from the flotation tailings. From the iron results it can be concluded that the GRA test procedure and XRF assaying can adequately predict CVD application and thus provide a quick tool for assessing potential CVD application for recovering gold bearing sulphides using indicator minerals. The GRA procedure is
capable of identifying the nature of the grade versus recovery relationship for continuous centrifugal concentration of sulphides. In this case the GRA procedure predicted inhibited gravity recovery for iron, which was exhibited by the CVD results.

3.6.2 Gold gravity release results

Due to particle sparsity, it is difficult to get reliable gold samples to use for Gravity Release Analysis and the presence of a single gold particle can greatly offset the metallurgical balance of the test. However, since gold is the target metal for the CVD application at Myra Falls, gold results obtained for the GRA procedure will be presented in this section. Table 3.4 shows the GRA results for gold.

<table>
<thead>
<tr>
<th>Product</th>
<th>Mass yield (%)</th>
<th>Grade (g/t)</th>
<th>Recovery (%)</th>
<th>Cumulative Recovery (%)</th>
<th>Cumulative Grade (g/t)</th>
<th>Upgrade ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Con # 1</td>
<td>1.8</td>
<td>4.1</td>
<td>12.6</td>
<td>12.6</td>
<td>4.1</td>
<td>7.0</td>
</tr>
<tr>
<td>Con # 2</td>
<td>1.6</td>
<td>1.8</td>
<td>4.7</td>
<td>17.3</td>
<td>3.1</td>
<td>5.2</td>
</tr>
<tr>
<td>Con # 3</td>
<td>1.7</td>
<td>1.4</td>
<td>4.0</td>
<td>21.3</td>
<td>2.5</td>
<td>4.2</td>
</tr>
<tr>
<td>Con # 4</td>
<td>1.6</td>
<td>1.0</td>
<td>2.8</td>
<td>24.0</td>
<td>2.1</td>
<td>3.6</td>
</tr>
<tr>
<td>Cleaner Tail</td>
<td>6.9</td>
<td>0.7</td>
<td>7.8</td>
<td>31.8</td>
<td>1.4</td>
<td>2.3</td>
</tr>
<tr>
<td>Tails</td>
<td>86.4</td>
<td>0.5</td>
<td>68.2</td>
<td>100</td>
<td>0.6</td>
<td>1.0</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>0.6</td>
<td>100</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The calculated results were used to generate a gravity release curve for gold, shown in Figure 3.10. From the release curve, the gold feed grade is 0.6 g/t and a concentrate of 2.2 g/t is obtainable at a recovery of 23 % and a mass yield of 5.8 %. This information is essential in determining which mass yield for the CVD will be adequate for a targeted metal recovery.
Figure 3.10: The gravity release curve for gold the dashed lines are the vectors whose gradient is a measure of grade.

To better understand the effect of mineralogy on the shape of the grade versus recovery curve it was assumed that the feed was composed of four major gold bearing mineral species. Species A has a high grade, low weight % and very high recovery rate and it represents the GRG, B has lower grade than A higher weight % and lower recovery rate and it represents the GRGS, C has negligible gold, high weight % and very low recovery rate represents gold associated with gangue and D has high gold grade, high weight % and very low recovery rate represent non-GRG rendered unrecoverable by gravity due to overgrinding. The weight percentage of each mineral, the gold grade in each mineral fraction and the recovery rates were modelled. Simulation results for the models are given in appendices C, D and E. Figure 3.11 shows the GRA grade versus recovery curve for gold representing three different mineralogical systems (models 1, 2 and 3). Model 1 represents the recovery of GRG for an ore consisting mainly of liberated gravity recoverable gold and gangue. Model 2 represents the recovery of gold existing as GRG and GRGS from gangue. Model 3, which best tracks the gold results, shows gold distributed in all four species. The results
show that the gold in Myra Falls tailings is mainly non-GRG and there is very low GRG and significant GRGS.

The model results are helpful to understand the bench scale tests. Selective gold recovery was achieved by gravity concentration on the Myra Falls flotation tail sample. A high-grade gold containing product was obtained in the first gravity concentration cycle, which represents recovery of mainly GRG. The gold grade decreased greatly after the first cycle due to the recovery of low-grade mineral fractions mainly the GRGS.

Figure 3.11: Grade versus recovery curve for gold in Myra Falls flotation tails.

The results indicate that gold lost to the final tailings at Myra Falls is partly recoverable by centrifugal concentration. Based on characterization of the gold by particle size, only 30 % of the gold in final tailings is above 38 μm, this could be the gold recoverable, whilst the 70 % would have been rendered non-gravity recoverable due to over grinding. The inhibited gravity recovery is similar to that exhibited by iron and can be attributed to un-liberated gold, locked in sulphides and gold rendered gravity non-recoverable due to over grinding. For purposes of comparing GRA results and CVD performance, the final cleaner tailings were considered as a 5th concentrate. The results are shown in Figure 3.12.
Figure 3.12: Comparison of GRA and select CVD optimum results based on NNREGA optimization for gold showing (a) variation of upgrade ratio with mass yield and (b) variation of recovery with mass yield.

The results show reasonable correlation of CVD and GRA results indicating the bench scale procedure can reliably predict CVD application. Iron results show better correlation than gold, as expected due to gold sampling and assaying errors. Figure 3.12 (b) shows that the GRA results form an upper envelop over the CVD results such that the recovery/mass yield relationship can be used for scaling CVD performance. The GRA procedure thus provides a mechanism of predicting the limit of gravity recovery for the CVD and can therefore be used for predicting potential CVD applications using small samples. Unlike the currently available laboratory scale techniques, the GRA is designed to cover a wider mass yield range and thus can easily be used to predict CVD performance for both low mass yields and higher mass yield applications. The experimental design for the GRA test procedure enables high mass yields to be tested without compromising the integrity of sample due to small sizes required to assess high mass yield. The GRA test results marks the upper limit of gold recoverable by the CVD from the flotation tailings.

Comparison of GRA results for gold and sulphides in Figure 3.13 shows that gold response to centrifugal concentration is superior to that of the sulphides as expected. Sulphur recovery is intermediate between iron and zinc, indicating it can be used as a measure of base metal sulphides recovery. The entire species exhibit a degree of inhibited gravity recoverability, attributed to particle size, degree of liberation and effective density.
Figure 3.13: Comparison of GRA results for gold and sulphides.

The GRA procedure can be used to both predict performance and the nature of response of an ore to centrifugal concentration. The weakness of the approach is its high sensitivity to tailing assay. A small variation in tailings grade drastically alters the shape and meaning of the grade versus recovery curve. Figure 3.14 shows the conceptual effect of variation of tailings grade from 0.5 to 5 % for iron. The results show that an error in measurement of tailings grade of magnitude equal to three can change the nature of response from limited recovery to fully recoverable. Therefore, strict care should be observed in preparing and assaying of the tailings, and duplicate tailings samples are recommended in order to ascertain repeatability and accuracy of the results. For gold, concentrate samples should be assayed to extinction.
Based on iron and gold results for Myra Falls, the GRA procedure has superior potential for predicting CVD application compared to the currently available bench scale procedures. The Gravity release curve predicts the upper limit for CVD recovery and shows the nature of response of the target minerals to CVD application. The GRA procedure and assaying using the XRF provides a quick CVD application assessment tool for gold bearing sulphides.

3.7 CVD performance assessment for an epithermal gold ore using the GRA procedure

In order to assess suitability of the GRA procedure for benchmarking CVD performance samples of CVD feed and tailings were collected from an operating mine treating an epithermal gold ore. The mine uses a CVD42 to scavenge for gold from flotation rougher tails. The ore comes from a high-grade epithermal hosted vein associated with quartz, calcite, sphalerite, galena and pyrite. From size assay results of the flotation tails, above 50% of the gold and 60% sulphides are in the -20 µm size fraction, which constitute above 50% of the plant tails, and is difficult to recover by gravity separation techniques.

In order to characterise the feed to the CVD A 100g representative sample of the flotation rougher tailings was riffled and analysed using X-ray diffraction (XRD) to determine the mineral occurrence. The Rietveld Topas 4.2 program was used for refining the X-ray powder-diffraction
data. Table 3.5 shows the results of relative amounts of crystalline phases normalized to 100%. The main difference between this ore and Myra Falls ore is that it contains significantly high silica and rhodochrosite and low pyrite. The presence of Actinolite, a low density iron bearing mineral, and low pyrite makes iron unsuitable as a proxy for sulphides, sulphur is more preferable.

Table 3.5: Rietveld analysis results.

<table>
<thead>
<tr>
<th>Mineral</th>
<th>Ideal Formula</th>
<th>% Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actinolite</td>
<td>Ca$_2$(Mg,Fe$^{2+}$)$_5$Si$<em>8$O$</em>{22}$(OH)$_2$</td>
<td>0.4</td>
</tr>
<tr>
<td>Calcite</td>
<td>CaCO$_3$</td>
<td>3.4</td>
</tr>
<tr>
<td>Clinochlore</td>
<td>(Mg,Fe$^{2+}$)$_5$Al(Si$<em>3$Al)O$</em>{10}$(OH)$_8$</td>
<td>4.9</td>
</tr>
<tr>
<td>Fluorite</td>
<td>CaF$_2$</td>
<td>1.3</td>
</tr>
<tr>
<td>Galena</td>
<td>PbS</td>
<td>0.1</td>
</tr>
<tr>
<td>Gypsum</td>
<td>CaSO$_4$·2H$_2$O</td>
<td>0.9</td>
</tr>
<tr>
<td>K-feldspar</td>
<td>KAlSi$_3$O$_8$</td>
<td>14.3</td>
</tr>
<tr>
<td>Muscovite</td>
<td>KAl$_2$AlSi$<em>3$O$</em>{10}$(OH)$_2$</td>
<td>2.5</td>
</tr>
<tr>
<td>Plagioclase</td>
<td>NaAlSi$_3$O$_8$ – CaAl$_2$Si$_2$O$_8$</td>
<td>1.4</td>
</tr>
<tr>
<td>Pyrite</td>
<td>FeS$_2$</td>
<td>0.5</td>
</tr>
<tr>
<td>Rhodochrosite</td>
<td>Mn$^{2+}$CO$_3$</td>
<td>18.4</td>
</tr>
<tr>
<td>Quartz</td>
<td>SiO$_2$</td>
<td>51.9</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>100</td>
</tr>
</tbody>
</table>

The GRA results are shown in the following section. The CVD performance assessment is based on comparison of gravity recoverable gold bearing sulphides in feed and tails. Figure 3.15 shows gold gravity release curves for CVD tails and feed.
The gravity release curves show that the feed grade for CVD feed and tail samples are not significantly different. There is, however, more gravity recoverable gold in the CVD feed than in tails as expected which is not apparent when comparing the grades for the two streams. The difference in the release curves account for the gold recovered in CVD concentrates, which is marginal. If a 30 % gold recovery is targeted, a concentrate containing 1.9 g/t and 1.1 g/t gold is recoverable for the CVD feed and tails respectively. From the shape of the release curve, it is evident that gold in the flotation rougher tails exhibit a degree of inhibition to gravity recovery, which is expected because of the fine particle size.

Figure 3.16 shows a comparison of the gravity recoverable gold in CVD feed and tails. The efficiency of the CVD in recovering gravity recoverable gold bearing sulphides can be estimated by the difference in the composition of gravity recoverable gold in CVD feed and tailings as measured by the GRA procedure, which gives a measure of the gravity recoverable gold which the CVD failed to recover.
For this application, the CVD is recovering about 18% of the gravity recoverable gold bearing sulphides present in the flotation tails. Sieve assay analysis of both streams showed a 10% decrease in weight for the fine fraction corresponding to 28% Au and 23% S for the same size fraction from CVD feed to tailings. This implies that the CVD is preferentially recovering gold and sulphides in the fine fraction, which is not expected. This anomaly can be attributed to gold association. If gold in fines is fully liberated or associated with sulphides and gold in coarser fractions is associated with light gangue minerals, the effective density of the coarser particles can be less than that of fines.

Sulphur recovery was used as a measure of base metal sulphides recovery. Figure 3.17 shows the Gravity Release Analysis results for sulphur. The trend is similar to that of gold, although there is a larger difference between gravity recoverable sulphur in CVD feed and tails. The results demonstrate the use of indicator minerals or elements (in this case sulphur) to predict gravity recoverable gold by continuous centrifugal concentration. Since the GRA procedure has been shown to reliably predict CVD application, the efficiency of an operating CVD can be measured by comparing the quantity of gravity recoverable target minerals in any two CVD streams.
3.8 The Gravity Release Index as a measure of amenability

The gravity recoverable gold (GRG) procedure is capable of distinguishing gravity recoverable and non-recoverable gold however; there is no mechanism of quantifying the extent of amenability from one mineral species to the next. Whilst many species can be recoverable by gravity, the ease of recovery is a function of machine characteristic, valuable and gangue mineralogy, degree of liberation, particle size and shape such that no two mineral particles can have exactly the same response to gravity. Unlike in flotation, where the rate constant can be quantified and used in process design based on laboratory studies, there is no parallel strategy in gravity concentration that can measure quantitatively the extent of mineral amenability to gravity. The gravity release index (GRI), introduced in this research is a way of quantitatively ranking the degree of gravity recoverability for different mineral species based on a quantity similar to flotation rate constant. This allows for ranking the easily recoverable and hard to recover particles by gravity. The GRI index is based on the Gravity Release Analysis procedure, which allows for fractional removal of concentrates, similar to the flotation tests described by Kelsall (1961).

3.8.1 First-order kinetics for Myra Falls flotation tails

For gravity recovery, if we assume a first order process, for a particular gravity recoverable mineral species at a concentration $C = C_0$ when mass yield is zero, integration leads to:

$$C = C_0 \exp(-kw)$$

3.1
where \( w \) is the mass yield, \( c \) is the concentration of gravity recoverable mineral remaining in tailings after a concentrate accounting to a mass yield of \( (w) \) has been separated from the feed and \( k \) is the GRI index, which gives a measure of gravity amenability. Three forms of the equation can be derived based on the GRA procedure.

\[
w(t) = w(0)\exp(-k_1 n) \quad 3.2
\]

\[
w(t) = w(0)\exp(-k_2 t) \quad 3.3
\]

\[
w(t) = w(0)\exp(-k_3 w_r) \quad 3.4
\]

where \( n \) is the number of concentration cycles, \( k_1 \) is the gravity concentration rate with unit 1/cycle, \( t \) is the cycle time, \( k_2 \) is the gravity concentration rate with unit 1/min, \( w_r \) is the weight of the sample, \( k_3 \) is the rate of gravity concentration with unit of 1/kg.

Figure 3.18 is a plot of weight remaining in the tailings for each stage of concentration. The gradient of lines gives the gravity release index, which is a measure of how easily the species are recoverable by centrifugal concentration. The straight lines indicate a constant rate of recovery whist the curve indicate more than one rate of recovery (Kelsall, 1961).

![Figure 3.18: Weight remaining versus gravity concentration cycle as a means of measuring gravity amenability.](image)

Gold has the highest amenability followed by iron then sulphur and lastly zinc, as expected, showing the effect of specific gravity on centrifugal separation, where the highest density particles are more susceptible to gravity concentration. The shape of the gold line shows
that there are at least two gold particle species being recovered, based on the two distinct gradients of the curve.

From this plot, the relative proportions of the easily recoverable and more difficult to recover species can be quantified. For the flotation tails at Myra Falls, the gold species more amenable to gravity accounts for GRG whilst the less amenable species are gold bearing sulphides. Quantification of relative abundance of the species is useful when deciding on whether to use batch or continuous concentrators for recovering the gold. When the gold bearing sulphides are more than the liberated gold species the CVD will be selected. The proportion of species is obtained from the y-intercept of the tangent to the low GRI species. In this case, it is estimated that above 90% of the Myra Falls flotation tailings gold is associated with sulphides or rendered non-gravity recoverable. Figure 3.19 shows the gravity release index ratio results for gold and sulphides obtained by dividing the gradients of lines in Figure 3.18 by mass of concentrate.

![Figure 3.19 Gravity release index ratio with respect to gravity concentration cycle: the dashed line shows the base line.](image)

Within margins of experimental error, based on repeat tests, the ratio is constant for all base metal sulphide species. A high ratio for gold at low mass yield indicates that the first MD3 run recovers mostly liberated GRG. As the mass yield is increased there is no significant difference between
gold and base metal sulphides GRI ratios, showing recovery of gold associated with base metal sulphides.

3.9 Myra Falls mineral association

To characterize the mineral species recoverable by the CVD, the CVD6 was tested at Myra Falls to treat cyclone underflow. Scanning Electron Microscopy analysis was performed to identify the gold species recovered by the CVD. To ensure that the SEM sample contained observable gold particles, 5 kg CVD concentrate was collected for further upgrading using the GRA procedure in order to concentrate the heavy fraction for mineralogical analysis. The GRA concentrates were combined and panned prior to mineralogical analysis. A Hitachi S3000N VP SEM with Energy Dispersive X-ray Spectroscopy (EDX) for elemental analysis using was used. The results are shown in Figures 3.20 and 3.21.

Figure 3.20: A scanning electron micrograph of Myra Falls gravity concentrate sample: Showing electrum labeled as Au, galena, pyrite, and gangue grains labeled as Si and composite particles containing electrum and sulphides
Figure 3.21: Myra Falls gravity concentrate EDX elemental maps showing association of gold and sulphides.
The SEM results show that gold exists as liberated electrum and un-liberated and associated with base metal sulphides. This validates the two gold species model predicted by the gravity release index. Galena is the main constituent of in the gravity concentrate from the cyclone underflow because it is still coarse enough to be recoverable by gravity and it has a high density. Some of the liberated gold particles exhibit a rod like shape, which suggests they may have been over ground.

3.10 Summary

The Gravity Release Analysis procedure developed in this research is capable of predicting CVD application by determining the maximum release of gold bearing sulphides using a representative small sample. By providing a measure of maximum gravity recoverable gold bearing sulphides, the procedure also provides a basis for benchmarking operating CVDs. The procedure is applicable for other continuous centrifugal concentrators and it is a useful tool for process design, which can boost application of the technology in mineral processing. Based on the Gravity Release Analysis procedure the Gravity release index (GRI) is introduced, which is a quantitative measure of gravity amenability. The GRI can predict the number of gravity recoverable particle species for gold and how amenable each particle type is to gravity recovery. It can be a useful tool for choosing between batch and continuous centrifugal concentration. With additional tests to calibrate the GRI, it can be developed into a standard quantitative measure for predicting potential continuous centrifugal concentration applications. The use of indicator minerals to assess amenability of gold bearing sulphides is demonstrated, which allows use of the XRF for assaying thus enabling quick assessment of CVD application using small sized samples.
Chapter 4: Development of a novel CVD optimization approach (NNREGA)

4.1 Introduction

The previous chapter dealt with the problem of finding a bench scale test to predict CVD application for an ore, and an indicative laboratory test procedure for assessing CVD application was developed and tested. Once gravity amenability is confirmed for an ore, the next stage is to run pilot scale CVD trials followed by plant trials. Currently, evaluation of the CVD is generally achieved through pilot scale testing a CVD6 (6- inch bowl CVD), which has a throughput of about 1 t/h. Testing involves selection of operating variable levels to achieve “optimum” product grade and recovery by varying one variable at a time. This technique can be misleading when the operating variables have interacting effects (Altun et al., 2006) and can result in running the CVD at sub-optimum variable settings, which makes application assessment ineffective.

McLeavy (2005) explored the effect of operating variables on the separation performance of the CVD by conducting factorial experiments on quartz/magnetite, and incremental testing (one variable at a time) on real ore on a zinc flotation cleaner tails stream at the Hudson Bay Mining and Smelting in Flin Flon Manitoba. By calculating the main effects and two factor interactions for the synthetic ore, the main machine variables for the CVD were found to be bowl speed and pinch valve timing (PVC and PVO). For the CVD6, fluidization water velocity was found not to have significant effect beyond 8 gal/min. Based on the incremental testing results, the Operating Variable Performance Ratio (OVP) which is a ratio of the slopes for grade versus parameter level/recovery versus parameter level was proposed as the basis for selecting which variable to change when fine tuning the CVD. The main weakness of the approach is varying one variable at a time and measuring the effect on one metallurgical response, such an approach fails to capture the effect of variable interactions on the two opposing metallurgical objectives (grade and recovery). The OVP approach is thus useful for moving along the operating line, but it does not provide a means to move from a sub-optimum region to the optimum grade versus recovery line. An approach, which captures the interaction of variables in CVD operations and the difference in individual optima for grade and recovery, is necessary.

Knowledge of the opposing relationship between grade and recovery has not yet been fully utilised in mineral processing optimization, as most of the approaches have targeted one response at time; either maximising grade or recovery and not simultaneous optimization of both responses.
Based on the grade versus recovery relationship, any approach, which yields one optimum point, is limited in depth and usefulness for mineral processing optimization (Al-Thyabats, 2008). The multi-objective simultaneous optimization used by Takahara (1997) to optimize sustained release formulation based on a distance function offers a better solution, recognising the opposing objectives in mineral processing optimization. However, formulation of the distance function would require an a priori weighting of the two objectives, based on some external parameter (most likely metal prices). The population approach used by Genetic algorithms allows for determination of the optimum grade versus recovery curve as the fittest offspring, without need of prior weighting of the objectives.

Hybrid ANN-Genetic Algorithm (GA) optimization is demonstrated in the literature reviewed, but the focus has been on optimization of neural network training (Nakhaei, Mosavi, and Sam, 2013) in order to avoid the time consuming trial and error method used in ANN training. A hybrid optimization approach that uses ANN for modeling followed by GA optimization, exploiting the capabilities in prediction and modeling of ANN and the surpassing optimization abilities of genetic algorithms has not yet been fully explored in mineral processing. However, other fields of study have been using the integrated approach for more than a decade (Chow et al., 2002; Cook et al., 2000; Gossard et al., 2013). Cook et al (2000) used a trained artificial neural network as the fitness function for evaluating individual chromosomes obtained by genetic algorithm optimization using the GeneHunter software. They optimized the internal bond as a measure of particleboard (a composite wood product) strength subject to ten operating parameters. Chow et al (2002) integrated ANN and GA to optimize the control of a central cooling system. The system consisted of five input variables and a single objective. ANN was employed to predict system outputs, which were used to evaluate the fitness function for genetic algorithm optimization. The most recent work by Gossard et al (2013) used a hybrid genetic algorithm and ANN to simultaneously optimize thermal conductivity and volumetric heat capacity of the external wall of a building to improve thermal efficiency. Two opposing objectives: reductions in annual energy consumption and summer comfort degree were simultaneously optimized. ANN simulation was used to evaluate the objective functions and NSGA (II), which is a Pareto genetic algorithm, was used for optimization. A similar approach was used by (Shen, Wang, & Li, 2007) to optimize an injection moulding processes and they stated that ANN was used to formulate an objective function for optimization using a genetic algorithm, but it is not clear how this was
achieved. The use of ANN as a fitness function has the advantage of providing a more accurate prediction of performance, but since ANN provides no mathematical relationship between control variables and output, unless network weights are gleaned to formulate a parametric model, no process understanding is gained. It is therefore necessary to provide a mathematical relationship linking the inputs and outputs in order to enhance knowledge of the process.

Regression models offer the process understanding which cannot be obtained from ANN. Mineral processing modeling has either been by regression or ANN and not both (Altun et al., 2006; Naik, Reddy, and Misra, 2005; Özgen et al., 2011; Aslan, Cifci, and Yan, 2008; Aslan and Fidan, 2008; Aslan and Ünal, 2009, 2011; Aslan, 2007, 2008a, 2008b; Celep et al., 2011; Hao et al., 2003; Jensen et al., 2004; Labidi et al., 2007; Jorjani, 2008a; Jorjani, 2008b and Al-Thybats, 2008). Jorjani et al. (2009) and Erzurumlu and Oktem (2007) compared the approaches and found ANN models were superior to regression in terms of accuracy of prediction as measured by the coefficient of determination. A combination of both ANN and regression to improve model prediction whilst retaining the parametric form has not yet been explored. The use of ANN for modeling is not novel, but its application for generating more uniform data to use in parametric modeling by identifying variation due to signal and thus reducing the effect of error on experimental results is new. This research proposes the use of regression models obtained from ANN simulation data as objective functions for genetic algorithm optimization instead of models generated from experimental data.

This chapter introduces a hybrid optimization approach, code named NNREGA, developed in this research through quartz/magnetite synthetic ore testing using a CVD6. The approach is an integration of artificial neural networks, regression modeling and genetic algorithm, to simultaneously optimize recovery and upgrade ratio for the CVD. NNREGA was developed with the aim of providing a tool for commissioning and auditing CVD operations. Figure 4.1 shows a schematic of the NNREGA procedure.
The initial stage of the test procedure is definition of the design space (also called operating region), which is the region contained by the maximum and minimum control variables level, and varies from machine to machine and is also application specific. Exploration of the design region is then performed using statistically designed experiments so as to determine how each parameter, and the combination of parameters affects recovery and upgrade ratio. The experimental results are used to train artificial neural network models to learn the relationship between predictors (bowl speed and pinch valve duration) and response variables (grade/upgrade ratio and recovery). The ramifications of purposefully taking the process out of or to the limits of control by adjusting control variables impose limitations on the extent to which variables can be adjusted in an
operating plant. A trained neural network is therefore an important tool for further exploration of the design space in order to understand the nature of the response surface. Off-line exploration of the design space using ANN simulation significantly reduces the number of necessary experimental tests to be conducted and consequently the cost and time for the test program. Although, ANN models are better at prediction, they do not provide much information about the relationship between variables and response. In order to define the fitness (objective) function for genetic algorithm optimization and better understand the effect of variables on response, mathematical models of recovery and upgrade ratio are developed from ANN simulation data using regression. The mathematical models are used to formulate objective functions to maximize recovery and upgrade ratio simultaneously. Instead of a single optimum point, the resultant solution is a set of non-dominated solutions of upgrade ratio and recovery, which gives the optimum recovery/upgrade ratio curve. Experimental validation of these results is conducted and the necessary adjustments done based on the validated results.

In order to assess the effect of machine variables on metallurgical performance, measured as a combination of grade and recovery, the non-machine related variables were kept constant. A synthetic ore composed of a known quantity of both magnetite and silica was used in developing the optimization procedure, this eliminated the effect of variation in ore characteristics (grade variation, liberation, and mineral association characteristics). (McLeavy, 2005) used the method of finding the main effects, introduced by Box and Draper (1987), and established that bowl speed and pinch valve timing were the main machine variables for the CVD. Therefore, for purposes of developing NNREGA the control variables were limited to bowl speed, pinch valve open duration and pinch valve closed duration.

### 4.2 Materials and methods

Sized synthetic quartz/magnetite ore was run in the CVD6. Silica from Lane Mountain was mixed with pure magnetite to constitute the synthetic ore. Coarse silica with a P80 of 600 μm and fine silica with a P80 of 212 μm was blended in the ratio 1:3 and mixed with sized 99 % pure magnetite to produce 2 % magnetite (low grade) which was later adjusted to 5 % magnetite for high grade tests after low grade tests were completed. The magnetite was mixed in the proportion of 1:3 + 425 to - 425 μm respectively. Water was added to the agitation tank to constitute a 30 % solids pulp, found to be optimum (McLeavy, 2005). A Davis tube was used to assay the CVD
product. The magnetite recovered for each run was returned to the conditioning tanks before proceeding to the next test in order to maintain the feed grade throughout the test program.

Representative samples of the feed for amenability testing were obtained by cutting the whole stream using a bucket during pilot testing. Results of preliminary gravity amenability assessment of the synthetic ore using the Gravity Amenability Test (GAT) are shown in Figure 4.2(a) and (b). The shape of the grade versus recovery curve shows that magnetite is amenable to separation from silica by centrifugal concentration. Increasing mass yield increased recovery showing upgrading of magnetite. Figure 4.2(b) is a comparison of magnetite recovery to a no upgrading line showing significant magnetite recovery.

![Figure 4.2: Gravity amenability test results for quartz/magnetite synthetic ore showing (a) a Grade versus recovery curve and (b) a comparison of magnetite Recovery/Mass yield and no upgrading.](image)

The pilot test work on synthetic ore was conducted at the Knelson Concentrators facility in Langley, BC. The main challenge faced when conducting these tests was maintaining a constant feed rate since the CVD was gravity fed from a mounted agitation tank. The pilot plant was therefore re-configured to include a recirculation pump, such that the feed to the CVD goes to a pump sump prior to pumping back to the agitation tank. A bleed was taken from the return pipe using a T-valve as shown in Figure 4.3, to feed the CVD6. There was still a noticeable decrease in feed rate as the feed tank height decreased below half, therefore only three to four tests were allowed per tank before pumping back the pulp from the holding tank to replenish the volume of the feed tank. To allow for constant pulp density, the feed tank was re-filled by pumping back the slurry from the holding tank after decanting.
Circumscribed central composite design was used to vary pinch valve open duration (PVO), pinch valve closed duration (PVC) and bowl speed (BS). Fluidization velocity was kept constant at 8 gal/min for all tests based on the findings of McLeavy (2005) that showed higher fluidization does not improve metallurgical performance. The feed rate was maintained at 1 tph throughout the test program.

4.2.1 Synthetic ore results

Figures 4.4 to 4.6 show quartz/magnetite CVD6 pilot tests results for 29 tests on 2 % magnetite and 34 tests on 5 % magnetite, the metallurgical balance tables are in appendix A and B. The graphs were obtained by averaging tests with the same parameter level for each variable in order to assess the effect of operating parameters on CVD performance.
Figure 4.4: The effect of varying bowl speed on CVD performance, showing magnetite grade (a), upgrade ratio (b) and recovery (c).

The error bars show variation in performance due to the other control variables. Figure 4.4 show results for the effect of bowl speed on concentrate grade (a), upgrade ratio (b) and recovery (c). The results show that varying bowl speed from 30 to 90 g has statistically significant effects on both magnetite concentrate grade and recovery. An optimum bowl speed, which maximizes magnetite recovery, exists between 45 and 80 g. Increasing bowl speed decreases both upgrade ratio and concentrate grade. Figure 4.4(a) is misleading, as it seems to show that the higher-grade ore outperforms the low-grade ore, however, the upgrade ratio plot overshadows the effect of
changes in feed grade and, shows that the lower grade ore is upgraded better by the CVD. It is clear from both plots that increasing the bowl speed reduces magnetite upgrading regardless of feed grade. However, if the ore grade increases from 2 % to 5 %, a change in bowl speed from 30 g at the lower grade to 90 g at the higher grade yielded concentrates of the same grade. When upgrade ratio is used as a performance measure, the change in metallurgical performance due to bowl speed is observable despite changes in feed grade as shown in Figure 4.4(b). Thus, when concentrate grade is used as a performance measure, if the feed grade is not constant, a genuine improvement in metallurgical performance can be rendered insignificant by a change in feed grade. Upgrade ratio was therefore selected instead of concentrate grade for NNREGA optimization since it is less sensitive to variation in feed grade. The results also show bowl speed quadratic effects for both upgrade ratio and recovery.

Figure 4.5 shows results of the effect of pinch valve closed duration on CVD performance. It is interesting to note that, unlike bowl speed, pinch valve closed duration had the same effect on both upgrade ratio and magnetite recovery. Increasing pinch valve closed duration increased both upgrade ratio and recovery until a peak was reached, after which further increase in PVC reduced both performance objectives.

Comparing Figure 4.5 to the results obtained by Klein et al (2010), two things are worth noting; (1) The operating range for pinch valve timing for the two machines differ by a magnitude of 10, which validates the uniqueness of machines and (2) The results in this thesis show a clear

![Figure 4.5: The effect of varying pinch valve closed duration on CVD performance, showing magnetite upgrade ratio (a), and recovery (b).]
recovery peak indicating quadratic effects, which is not so clear in Klein et al (2010). This may indicate that the range tested by Klein et al (2010) did not cover the complete possible PVC operating range for the unit they tested. The optimum PVC for this application was in the range of 10 – 15 s.

Figure 4.6 shows results of varying pinch valve open duration on CVD performance. Increasing PVO reduces upgrade ratio, due to increase in the proportion of particles that bypass upgrading and report to CVD concentrates. Enough open time should be allowed to discharge only the upgraded layer of particles. When PVO is increased beyond a critical level, dilution of concentrates by gangue bypass reduces upgrade ratio rendering recovery constant. Thus a peak also exists for recovery as a function of PVO, and the relationship exhibit quadratic effects.

![Figure 4.6: The effect of varying pinch valve open duration on CVD performance, showing magnetite upgrade ratio (a), and recovery (b).](image)

The synthetic ore results show that the three CVD control variables have quadratic effects on both grade and recovery. These results were used to select second order regression models for optimization. Upgrade ratio is less sensitive to variations in feed grade for fully liberated ores, therefore it is a better performance indicator than concentrate grade for purposes of optimization.

### 4.3 The NNREGA algorithm

The NNREGA algorithm shown in Figure 4.7 is an iterative hybrid optimization approach incorporating ANN for simulation, regression modeling and genetic algorithm for optimization.
The application of each of the tools individually has been demonstrated in literature and the following section describes integration of these approaches into the NNREGA optimization
approach. Whilst this research focussed on just the CVD, the approach can be expanded to optimize any mineral processing unit process with multiple interacting control parameters.

The initial stage involves defining the design space (possible parameter level range and their combinations) and selecting suitable performance objectives. Then the design space is strategically explored using statistically designed experiments in order to acquire experimental data for ANN training. Generally, artificial neural networks require a lot of data for training, which is expensive to obtain in mineral processing due to the high cost of assaying. Part of the novelty of the NNREGA optimization approach is a reduction in the number of experimental tests required to explore a design region by using statistical experimental design.

While obtaining data for neural network training is economically demanding for commissioning purposes, once installed, the process control data which is readily available to operators can be channelled towards training ANN to better understand process dynamics through simulation. This approach is a positive step towards running a process not only to obtain the product but also to obtain useful data, which enables a better understanding of the process.

4.3.1 Defining the design space

Prior to any statistical design experiments, the design space has to be defined and the performance measures selected. Each application is unique in terms of ore characteristics, pulp density and feed rate. In addition, no two machines are identical such that there is need to determine the operating range for pinch valve timing for each machine.

The approach for determining parameter ranges is based on knowledge of the effect of control parameters and their consequent interaction gained from literature (Ghaffari, 2004; Klein et al., 2010; McLeavy, 2005; Mcleavy, Klein & Grewal, 2001) and the synthetic ore results. Mass yield was used as the response variable for purposes of the scoping tests to determine the operating range for the design variables. To assess the variation of control parameter range between different concentrator units, two CVD6 units were tested on the quartz magnetite synthetic ore. Since there were no down processes intended for the pilot test product for synthetic ore tests, an arbitrary maximum mass yield of 65 % was used. Table 4.1 shows the range of the control variables obtained for two units of the same model (CVD6) tested on quartz/magnetite synthetic ore.
Table 4.1: Control variable range for two CVD6 units

<table>
<thead>
<tr>
<th>Unit</th>
<th>Level</th>
<th>PVO (s)</th>
<th>PVC (s)</th>
<th>BS (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Minimum</td>
<td>0.15</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.5</td>
<td>20</td>
<td>90</td>
</tr>
<tr>
<td>B</td>
<td>Minimum</td>
<td>0.03</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>0.09</td>
<td>20</td>
<td>90</td>
</tr>
</tbody>
</table>

These results demonstrate how parameter range settings can vary drastically for the same size of machine due to manufacturing tolerance. Indicating that even the testing range of parameters cannot be blindly applied to a new installation. There is therefore need to determine the parameter limits prior to optimization.

(a) Bowl Speed (BS)

The operating manual for the CVD recommends bowl speed (the speed of rotation) in the range 30 - 90 g, which converts to 581-1007 rpm for the CVD6. The actual rotation rate that yields the requisite bowl speed depends on the clearance of the proximity sensor (motion sensor which measure motor speed) from the motor plate, which is dependent on the operator commissioning the machine. The sensor is mounted during machine installation and the clearance can vary from one installation to another. Preliminary results showed that the CVD6 could be operated at 20 g and yield good results in some applications; therefore, the testing range for bowl speed can be from 20 g to 90 g. However, for some applications tested in this research, especially for full-scale plants, it was impossible to test machine performance beyond 80 g as the machine became unstable due to high vibration. Thus, the bowl speed range is also application specific.

(b) Pinch valve open duration (PVO)

The PVO depends on the pneumatic system (compressor, valves and airlines), which is unique for each CVD unit. Since high bowl speed increases mass yield, in order to obtain the lower limit for pinch valve open duration, bowl speed is set to 90 g and PVC set to 15 s. The PVO is lowered until mass yield is just above the percentage composition of mineral of interest in the feed, which marks the pinch valve lower limit. To get the upper limit for PVO, The bowl speed is set to 30 g and the open time is increased until the mass yield equals the capacity for intended
downstream processes. Current CVD applications involves mainly scavenging, and since the CVD concentrate has to be further treated by another unit process, a limit is imposed on the CVD concentrate tonnage by the capacity of the down process.

(c) Pinch valve closed duration (PVC)

PVC is also a function of the pneumatic system. To obtain the PVC lower limit the PVO is set to the lower limit and bowl speed to 30 g whilst the PVC is lowered until the mass yield equals the capacity for the intended downstream application. To get the upper limit for the PVC, The bowl speed is kept at 90 g, PVO adjusted to the upper limit and kept constant whilst the pinch valve closed duration is increased until the mass yield to concentrate is just above the percentage composition of mineral of the interest in the feed.

4.3.1.1 Selection of performance measures

Equally important to CVD optimization is the choice of performance measures. Standard performance measures for evaluating process efficiency include recovery, concentrate grade, upgrade ratio, ratio of concentration and metallurgical balance (Vasudevan and Nagaraj, 2012; Aplan, 2003). Separation efficiency, which measures the difference between the recovery of valuable metal and waste in concentrate, and is frequently represented by the partition curve (fractional recovery curve), is often used as a measure of the effectiveness of gravity concentration. The efficiency in separation is measured by the probable error ($E_p = (d_{25} - d_{75})/2$) or by the sharpness index ($d_{75}/d_{25}$), which is a measure of the slope of the partition curve. The separation efficiency is a function of both the separating device and mineral specific characteristics (Aplan, 2003). Economic factors also influence selection of optimum metallurgical performance, although they usually do not influence the technical effectiveness of the beneficiation process. However, in recognition of the centrality of economic factors in deciding a more desirable performance, a combination of concentrate grade and recovery is a preferred measure for evaluating CVD performance. The NNREGA procedure allows for determination of different combinations of grade and recovery, which are non-dominated, and leaving the decision of where to operate on the optimum grade versus recovery curve to the operator based on variations in economic factors.
The already known conflicting grade versus recovery relationship is used as the basis of metallurgical performance in the NNREGA procedure. As seen in chapter 3, the shape of the curve is a function of mineral characteristics, however the boundary line (operating line) is a function of both mineralogy and machine performance.

Figure 4.8 shows conceptual graphs of the effect of gravity recoverable gold bearing sulphides (GRGS) on concentrate grade and upgrade ratio, assuming bimodal gold bearing particles. Since the CVD is used to scavenge gold from plant tailings at Myra Falls gold in final tails would have evaded two batch Knelson concentrators it is reasonable to assume that liberated gold reporting to the final tails would have been rendered non-gravity recoverable by over-grinding. Such that the only gold bearing species recoverable by gravity in the plant tails will be gold bearing sulphide middlings. Some of the free gold, although rendered non-gravity recoverable, can still be recovered in CVD concentrate due to mass splitting. Figure 4.8 (a) shows that when feed grade and GRGS is constant, CVD concentrate and tailings grade essentially remains constant such that upgrade ratio do not change. Figure 4.5 (b) shows increasing feed grade due to increasing non-gravity recoverable gold, tailings grade increases with increasing feed grade, such that even though concentrate grade may remain constant, upgrade ratio decreases. When feed grade increases due to increasing GRGS (c), concentrate grade will increase whilst upgrade ratio and tailings grade remains constant. Feed grade may remain constant whilst the proportion of GRGS increases (d) or decreases (e). This may render optimization tests futile as the effect of changing parameter levels may either be diminished or increased, leading to an inaccurate assessment of the effect of variables. It is crucial to state that both upgrade ratio and grade are poor performance indicators under such conditions. However, when ore mineralogy is constant such changes are not expected. Concentrate grade is misleading as a performance measure for (c), since it accounts for the seemingly increase in performance which is a function of mineralogy and not control parameters. Both grade and upgrade ratio are good indicators if the grade and GRGS is constant, whilst concentrate grade is a better performance measure for optimization when increasing feed grade is a result of increase in non gravity recoverable gold (b). Whilst this conceptualization helps in understanding the contribution of GRGS and how it can lead to erroneous optimization results when using grade or upgrade ratio, real ore has a combination of these conditions, which complicates the optimization process.
Figure 4.8: A conceptual representation of the effect of GRGS on gravity concentrates considering repeat tests and variations in ore characteristics.
Figure 4.9 shows the conceptual graphs showing the effect of variation in feed grade as a result of variation in the GRGS on concentrate grade and upgrade ratio. If the GRGS is constant and feed grade is constant, either grade or upgrade works as performance indicators. When tailings grade increases with increasing feed grade due to increase in non-GRGS, concentrate ratio is a better performance measure for purposes of optimization. When GRGS increases as the feed grade increases, the tailings grade should remain essentially constant and the upgrade ratio becomes a better performance indicator for optimization tests.

![Figure 4.9: Effect of feed grade variation on concentrate grade and upgrade ratio. Each performance measure is superior for optimization only when it is constant as the feed grade varies](image)

Figure 4.10 shows results of feed grade variation on Myra Falls final tails based on iron results. As shown in chapter 3, iron is a good indicator of pyrite and sulphides recovery in the Myra Falls ore. For the repeat runs, tailings grade remained essentially constant as the feed grade increased, therefore the increase in feed grade is attributed to increase in GRGS such that upgrade ratio becomes a superior performance measure for this application.
Figure 4.10: The relationship between feed grade and tailings grade for Fe recovery for Myra Falls tails based on repeat CVD6 tests, which is typical type c in Figure 4.8.

Concentrate results shows a seemingly increase in performance from test 1 to 4, but the upgrade ratio results clearly show that there is no difference in performance for the 4 tests. This serves as the basis of selecting upgrade ratio as a performance measure for the NNREGA optimization procedure.

4.3.2 Statistical plant experiments

Once the performance measures are selected and the boundary values for control parameters have been defined, experimental exploration of the design space is achieved by statistical experimental designs. Selection of experimental designs is a balance of cost and maximum exploration of the design region. To assess the effect of combinations of extreme control variable levels on upgrade ratio and recovery; $2^3$ factorial experimental matrixes with two
centre points to test lack of fit is employed. The actual parameter levels are obtained by converting the variable levels into coded values using Eq. 4.1:

\[
x_i = \frac{X_i - X_{AV}}{(X_{UB} - X_{LB})/2}
\]

\[
X_{AV} = \frac{X_{UB} + X_{LB}}{2}
\]

where \(x_i\) is the coded value for a variable level, \(X_i\) is the actual level of variable \(x\), \(X_{UB}\) is the actual variable upper limit, \(X_{LB}\) is the actual variable lower limit, \(X_{AV}\) is the actual variable mean.

4.3.2.1 Circumscribed central composite design (CCCD) experiments

To further explore the design region and generate adequate data for artificial neural network training, second order experimental design experiments are conducted. Circumscribed central composite designs provide better exploration of the design region with the minimum number of experimental runs. CCCD experiments are able to generate results at 5 variable levels with a minimum number of experimental runs and are preferred over other second order designs like the Box-Behnken design which requires less experimental runs but only generate results for three variable levels. Full factorial design would require 243 experimental runs to explore an equivalent design space and is unsuitable for such applications where the cost of assaying is high. Table 4.2 and Figure 4.11 show the design matrix and the graphical exploration of the design space for circumscribed central composite design (CCCD) showing factorial design, star points and repeat centre point runs. The star runs enable further exploration of the experimental region. Repeat center point runs are for error analysis and can be varied depending on availability of resources. Conversion of actual parameter levels to coded levels is achieved using Eq. 4.1.
Table 4.2: Circumscribed central composite design matrix

<table>
<thead>
<tr>
<th>PVO</th>
<th>PVC</th>
<th>Bowl Speed</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>-1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>1.682</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>-1.682</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>-1.682</td>
<td>0</td>
<td>Star design points</td>
</tr>
<tr>
<td>0</td>
<td>1.682</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>-1.682</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1.682</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Repeat centre runs</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.11: Graphical representation of Circumscribed central composite design showing the maximum exploration of the design space

4.3.3 ANN modeling and simulation

Mineral processing sampling is prone to error especially sampling of gravity concentration. Gold nugget effect and particle sparsity effect present sampling problems not common to other minerals. Particle sparsity effect, defined as the effect resulting from low number of gold particles such that the analysis of a sub-sample depends more on the chance occurrence of gold particles in the analytical portion than the actual concentration within a sample (Clifton et al., 1969), is the main challenge. Such that, the presence of coarse gold nuggets invalidates small sample assays (Bacon, Hawthorn, & Poling, 1989). Tests aimed at identifying superior variable setting, can be rendered futile by the gold nugget effect and particle sparsity effect, by offsetting assays resulting in misleading conclusions on the superior variable settings. The CVD application for scavenging, targets gold middlings and is thus spared the problems associated with sampling gold nuggets but the sparsity effect has to be dealt with. In this research, indicator sulphide mineral assays were used instead of gold. However, variation in feed grade and sampling error result in noisy
experimental data, which need to be smoothened prior to regression modeling, otherwise it becomes increasingly difficult to select the most appropriate model as most of the regression models will not satisfy both the significance and lack of fit tests. ANNs can determine the trend for the effect of control variables on the performance characteristics, which would otherwise be impossible to determine by parametric methods and are therefore used in the NNEREGA approach.

ANNs are composed of simple elements (neurons) that operate in parallel and they can either be single or multi layered. Each node in the network has two important features, an input function (associated with a predictor variable) and an activation function. A bias node with a constant value of one is added to the input nodes to introduce an additional degree of freedom. Squashing functions are used as activation functions for the nodes to produce signal strength between 0 and 1 or between -1 and +1. These can be either threshold functions that allow a signal to pass or they can be a linear or nonlinear function such as sigmoid, sine or hyperbolic tangent functions. Multilayered networks are able to compute a wider range of functions, however they require more computational effort to find the correct combination of weights as the topologies become increasingly complex. Network topologies include, Multilayer perceptron, Kohonean self-organizing feature maps, Carpenter/Grossberg classifiers, Hamming nets and Hopfield nets, and have been reviewed elsewhere in literature (Van der Walt, 1993). Feed-forward back-propagation networks have proven capabilities to approximate functions similar to those expected for the CVD (Hornik et al., 1989, Van der Walt, 1993; Jorjani, 2008). The most popular activation function for back-propagation networks is the sigmoid function shown in eqn. 4.3 (Van de Walt et al., 1993).

\[ s_c(x) = \frac{1}{1 + e^{-cx}} \]  

4.3

The value of \( c \) is arbitrary and serves to alter the shape of the sigmoid function. As it approaches infinity, the sigmoid converges to a step function at the origin.

Connections weights between neurons determine the accuracy of prediction for ANNs, and they are adjusted during training to achieve the best fitting model. Training error, gradient of error or cross validation are used as convergence criteria during network training. Although cross validation is more reliable, because it is computationally more demanding and often requires more data, the error function is usually used. Various error functions can be used, but the most common stopping criterion is the least mean square error function (MSE). The set of weights that minimizes this error function is considered to be the solution of the learning problem. The number of hidden
neurons in a network determines its learning and generalization ability. Too many hidden neurons lead to over-fitting and thus poor generalization, whilst few hidden neurons lead to poor learning and therefore lack of fit.

Artificial neural network design involves selecting the network architecture, topology, data representation, training algorithm, training parameters, and terminating criteria to obtain a desired level of performance (Twomey and Smith, 1995). It is essential to get the right size of network to ensure both generalization and good fit. Considerable research has been done to determine possible relationships between the number of neurons in a hidden layer and input and output layers (Jadid and Fairbairn, 1996; Latchtermacher and Fuller, 1995; Masters, 1994; Hecht-Nielsen, 1990; Upadhaya and Eryureka, 1992; Widrow and Lehr, 1990). However, later work by Basheer and Hajmeer (2000) maintains that the most popular approach to determining the number of hidden neurons is still trial and error. In their study, they observed that the error function for testing attains a minimum as the number of hidden layers and training cycles are increased, indicating the best neural network. A commercial Matlab version 7.10, ANN toolbox software was used in this study for designing, training and testing CVD artificial neural networks. Hornik et al (1989) proved from first principles that feed-forward back propagation networks with one hidden layer are able to approximate any function to any desired accuracy, provided there are sufficient hidden neurons. Therefore, one hidden layer networks were considered adequate for the CVD ANN modeling problem.

In a feed forward back propagation neural network, neuron activation flows from the input layer, via the hidden layer(s), to the output layer. Supervised iterative training methods, which can either, be batch or incremental, searches for the minimum error function in weight space using the method of gradient descent by applying the delta-learning rule. The approximation error is calculated and propagated backward from output to input layers and is used to update the network weights (Torrecilla et al., 2007; Zheng et al., 2007; Madadlou et al., 2009). Each adjustment of weights is an epoch. The error signal determines the degree of change of weights on each learning cycle as shown by eqn. 4.4.

\[ x_{k+1} = x_k - \alpha_k g_k \]  

4.4

where \( x_k \) is the current weight and biases, \( g_k \) is the current gradient and \( \alpha_k \) is the learning rate.

The Levenberg Marquardt (LM) algorithm, used in this research, is an adaptive minimization method, used to speed up the convergence of the backpropagation-learning
algorithm by combining gradient of descent and Gauss-Newton method. In order to learn associations between specified input-output pairs, the algorithm adjusts the network bias and weights in order to minimize the mean square error (MSE) between the network prediction and training datasets. The algorithm is code-named trainlm in the Matlab 7.10 Neural Network Toolbox. It uses Newton-like updates to adjust network weights and biases by applying a Jacobian matrix (matrix of first order partial derivatives of a function) to approximate the Hessian (H) matrix (matrix of second order partial derivatives describing the local curvature of a function of many variables). Eq. 4.5 gives a reasonable approximation of the Hessian matrix for the sum of squares error function, which is used in feed-forward back-propagation network training:

\[ H = J^T J \]  
\[ g = J^T e \]  
\[ x_{k+1} = x_k - \left[ J J^T + \mu I \right]^{-1} J^T e \]

The gradient is computed using eqn. 4.6 where \( g \) is the gradient, \( J \) is the Jacobian matrix containing the first order derivatives of the network errors with respect to weights and biases, \( \mu \) is the step size and \( e \) is the vector of network errors. Equation 4.7 shows the LM algorithm iteration. When close to an error minimum, the Levenberg-Marquardt algorithm shifts to Gauss-Newton’s method (which is faster and more accurate near an error minimum) by reducing the step size (\( \mu \)) in Eq. 4.7 and when far from the optimum, it acts like the gradient descent method, increasing the step size. The LM algorithm is the fastest method of training moderately sized feed-forward neural networks (Matlab, 2010a), but does give memory problems for large networks. A more complete description including examples can be found elsewhere in literature (Gavin, 2011; Hagan and Menhaj, 1994; Marquardt, 1963; MathWorks, 2003). The networks trained in this research are relatively small and less computationally demanding, therefore the LM algorithm was considered suitable.

For the NNREGA approach the network architecture consists of an input layer with three neurons corresponding to the three input variables (PVO, PVC and BS) for the CVD, one hidden layer with select number of neurons, and an output layer of one neuron corresponding to either upgrade ratio or recovery. The network topology is shown in Figure 4.12.
To improve training efficiency a mapminmax function, which scales the variables between [-1, 1] was used to pre-process the variables before training. An early stopping technique is applied to avoid overtraining the network and compromising generalization. Using this technique the experimental data is randomly divided into three subsets after removing outliers. These sets consist of 60% training, 20% validation and 20% testing data. The training subset is used for computing the error gradient and updating the network weights and biases. The error on the validation subset is monitored during network training to avoid overfitting. The validation error normally decreases during the initial phase of training and begins to increase at the onset of overfitting, while training error continues to decrease. When the validation error increases for a specified number of iterations (four in this research), training is stopped, and the weights and biases at the minimum of the validation error are retained. Testing error is used to measure the ability of the network to generalize and also assess division of data, if the error in the test set reaches a minimum at a significantly different iteration number than the validation set error, there will be poor division of data. The selected best network is the one, which not only has a high $R^2$ for training, validation and testing, but that with the lowest MSE too. Predicted results are plotted against observed and the value of the coefficient of determination and residuals are used to decide when the trained network is adequate.
The trained network is then used for simulation in order to further explore the design region. The design region can be subdivided and combinations of variable levels can be generated randomly for simulation Al-Thyabats (2008). Alternatively, random combinations of variables levels between the variable boundary levels can be generated using the excel function randbetween, and the result used as input to explore the design region by simulation. Incremental testing proposed by McLeavy (2005) using the OVP approach can be used to find the control variable levels to be used for simulation. For purposes of testing the NNREGA approach only variable levels used in the statistical experiments were simulated.

Although ANN has better prediction, the failure to provide a deterministic relationship between the input and output, which is necessary when defining the optimization problem, negates its usefulness for the CVD problem. In order to capture the advantages of both ANN and parametric models, NNREGA uses the ANN simulation data as seed for parametric modeling, which is novel. Thus, ANN simulation smoothen the experimental data for regression modeling.

4.3.4 Regression modeling

In order to obtain mathematical models that adequately describe and predict process behaviour for process optimization stepwise regression modeling was employed. The aim was to formulate a multi-objective optimization problem in recovery and upgrade ratio as a function of the control parameters. ANN simulation data was used to model upgrade and recovery functions subject to PVO, PVC and BS.

ANN simulation data was subjected to stepwise multiple linear regressions using the EREGRESS (Essential Regression) program to model recovery and upgrade ratio. Analysis of variance (ANOVA) and graphical residual analysis was used to assess the quality of fit for the regression models. The central idea of ANOVA is to compare variation due to treatment (change in the combination of variable levels) with the variation due to random errors inherent to the measurements of the generated responses and thus evaluate the significance of the regression. Replicates of select points are used to estimate pure error associated with repetitions. The Fisher distribution (F test) is used to assess how well the model fit the simulation data by comparing the ratio of regression mean squared error to residual mean squared error (MSE_{regress}/MSE_{residual}) with tabulated values for (F), where (MSE) is the mean squared error.

It is worth noting that the regression models being generated are in actual fact models of models and therefore have tendency to propagate the error of the ANN models. However,
considering the accuracy of the ANN models (which yielded on average an $R^2$ value above 0.9), the error being propagated is smaller compared to the random error due to measurement, therefore, the approach is considered acceptable.

### 4.3.4.1 Model discrimination

The task of modeling includes selection of the most appropriate model from rival models. A model discrimination procedure similar to the one proposed by Chen and Asprey (2003) was adopted in this research to select the best model. Models of varying orders were fitted to the data, and a number of performance indicators including coefficient of multiple determination ($R^2$), adjusted $R^2_{adj}$, F test, p-value, t-test and variance inflation factor (VIF) were applied to the models and the best model was selected. The coefficient of multiple determination given in equation 4.8 shows the proportion of response variability observed within the variable value ranges tested, which can be explained by one or more of the variables and interactions considered in the model.

$$R^2 = 1 - \frac{SS_E}{SS_T}$$  

Since $R^2$ always increases when a new variable is added due to increase in the regression sum of squares, it can be difficult to judge whether the increase is an improvement in model fitting or over fitting (including regressors that are not really useful). The adjusted coefficient of multiple determinations given in equation 4.9 incorporates the degrees of freedom and therefore only increases when a variable added to the model reduces the mean squared error. Both $R^2$ and $R^2_{adj}$ were used to determine model adequacy in order to prevent over-fitting. A small difference in magnitude between $R^2$ and $R^2_{adj}$ indicate there is no over-fitting.

$$R_{adj}^2 = 1 - \frac{SS_E/(n-p)}{SS_T/(n-1)}$$  

The Fisher distribution (F-test) is used to assess how well the model fit the experimental data by comparing the ratio of regression mean squared error to residual mean squared error ($MS_{regress}/MS_{residual}$) with tabulated values of $F$. A low probability (p-value) shows a high significance of the regression model (Adinarayana & Ellaiah, 2002; Akhnararova & Kafarov, 1992). The procedure partitions the total variability ($SS_T$) in response variable into two components: sum of squared error ($SS_E$) and regression sum of squares ($SS_R$) as shown in equation 2.10.
\[ SS_T = SS_E + SS_R \]

If the null hypothesis is true, the statistic

\[ F_0 = \frac{MS_R}{MS_E} = \frac{SS_R / k}{SS_E / (n - 2)} \]

follows a \( F_{k,n-p} \) distribution and the null hypothesis is rejected if \( F_0 > F_{\alpha,k,n-p} \). Model significance is determined by testing the hypothesis that none of the regressors account for the variation in the response. Similar conclusions can be drawn using t-statistic. The tests are similar but the t-test is more flexible and it allows testing in one-sided alternative hypothesis.

To determine significance of individual coefficients, the null hypothesis, \( H_0: B_j = 0 \) is tested using the t-test. The null hypothesis is rejected if: \(|t| > t_{\alpha/2,n-p}\), where

\[ t_0 = \frac{\hat{B}_j}{\text{Se}(\hat{B}_j)} \]

Alternatively, the p-value at a given significance level (\( \alpha \)) can be used to draw the same conclusion. For a model to be significant it should have a high \( F_0 \)-value and a low p-value. The most used significance level is \( \alpha = 0.05 \) which means that the hypothesis of an adequate model will only be rejected in 5 % of tests for which the model really is adequate. It is worth noting that the regressor variables also depends on other regressors and thus the test is regarded as a marginal test (Montgomery & Runger, 2002). In this research, both the recovery and upgrade ratio models were assessed for significance and lack of fit tests using ANOVA analysis. Since the parameters are estimated from experimental data, which is subject to error, the estimates are to be accompanied by a confidence interval (C.I.), which is the region in which the true values are expected to lie with a given level of confidence. The 95 % C.I. was used in this research.

Residual analysis based on the assumption of normal and independently distributed error with a mean of zero and some constant variance was also used to graphically assess the adequacy of regression models. A regression model is expected to err in predicting a response in a random fashion; the model should predict values higher than actual and lower than actual with equal probability. In addition, the level of the error should be independent of when the observation occurred in the study, or the size of the observation being predicted, or even the factor settings involved in making the prediction. The overall pattern of the residuals should be similar to the bell shaped pattern observed when plotting a histogram of normally distributed data. Deviation from
these assumptions means that residuals contain a structure, which is not accounted for by the regression model, implying the model will be inadequate. This approach is efficient at discriminating models with high coefficients of determination; where over fitting may not be obvious using alternative approaches.

The best recovery and upgrade ratio models are used to formulate optimization objectives to maximize CVD metallurgical performance.

4.3.5 Multi-objective genetic algorithm optimization

Recent applications of genetic algorithm optimization in mining and mineral processing has attempted to optimize coal preparation plants with the objective to maximize overall revenue by searching the best combination of overall yield and multiple product quality constraints (Gupta et al., 2007). The optimization program generated grade versus recovery data using model equations for each circuit and then the optimal yield for maximum revenue was determined. Although, this was more of a financial model than technical, the concepts are applicable to determination of optimum parameter settings in order to achieve the best combination of grade or upgrade ratio and recovery for the CVD. Pareto optimization, used in the NNREGA procedure, was successfully used by Pirouzan, Yahyaei, and Banisi (2012) to optimize flotation cell configuration using parametric equations based on flotation rate constant. In this research, the multi-objective solver, gamultiobj in Matlab 2010 was used for the simultaneous optimization of recovery and upgrade ratio.

Implementation of a genetic algorithm (GA) begins by creating a random population of chromosomes (combination of possible solutions within the solution space), evaluating the structure, and allocating reproduction opportunities (fitness function) in such a way that chromosomes representing better solutions to the target problem are given more chances to reproduce than the chromosomes which are poor solutions. Each generation of possible solutions evolves from the previous one and the overall fitness function of the population should show improvement. The GA randomly generates an initial population \( P^0 \) or a priori knowledge is used to seed it with good chromosomes to commence iteration. The GA applies genetic operators of selection, crossover, and mutation to population \( P^k \) to produce population \( P^{k+1} \).

For the canonical genetic algorithm, selection of the best chromosomes to take part in creating the next generation is done on the basis of the fitness function \( f_i / f_{ave} \), where \( f_i \) is the
value of the objective function associated with string \((i)\) and \(f_{ave}\) is the average value of the objective function in the population. The objective function, also referred to as evaluation function, provides a measure of performance with respect to a set of parameters. The fitness function transforms that measure of performance into an allocation of reproductive opportunities. Different selection schemes are available and the most common are ranking (Baker, 1985; Whitley, 1989) and sampling methods such as roulette-wheel, stochastic and tournament selection (Goldberg, 1990). Scaling functions based on the position of an individual member of the population or the fitness function score convert raw scores to values in the range suitable for the selection function.

Reproduction functions determine how the genetic algorithm creates child solutions for the new generation. The elite count specifies the number of children surviving to the next generation and is an integer less than or equal to the population size. The higher the elite count, the higher the exploitation. Crossover and mutation increases exploration of the design region therefore preventing premature convergence. However, to maximize the preservation of superior solutions after selection, the disruptive effects of crossover and mutation should be minimized (Whitley, 1994). Mutation acts as a background operator and enables the population to regain diversity.

The genetic algorithm tends to converge to a single solution due to stochastic errors associated with genetic operators (Deb & Goldberg, 1989). To avoid this there has to be a diversity preservation operator. Several approaches have been proposed including the sharing function (Goldberg and Richardson, 1989), the crowding operator (Holland, 1975), which was further developed by DeJong (1975), Deb and Goldberg (1989) into generation gap and crowding factor operators, and other approaches reviewed by Coello (2000). In the Matlab GA toolbox used in this research, the crossover fraction determines the generation gap (which indicates the percentage of population allowed to reproduce). The crowding factor specifies the number of individuals initially selected to be replaced by a particular offspring and is controlled by the elite count. The crowding distance approach proposed by (Deb et al., 2000) and used in the Matlab toolbox is similar to the sharing distance in that it is used to discount candidate solutions from inclusion in the surviving population based on the closeness in the objective space of the candidates.

For the \(NNREGA\) approach, the initial population is generated randomly using a creation function subject to boundary constraints. A non-dominated rank is assigned to each individual using the relative fitness. The combination of parameters yielding the highest combination of recovery and upgrade ratio has the highest rank and is assigned to the first front. The solver uses a
controlled elitist genetic algorithm, a variant of the non-dominated sorting genetic algorithm, and referred to as NSGA-II (Deb et al., 2002). This method uses two attributes: non-domination rank for convergence, and crowding distance for a diversified Pareto solution. The distance measure, (which is how far in the objective space a solution is from the other with the same rank) is used to compare individual solutions with similar performance. After the first generation, subsequent generations are produced using an elitist procedure, different from a single objective genetic algorithm optimization.

The pseudo code for the unique feature of the multi-objective optimization is shown below, where $P_t$ is the parent population and $Q_t$ is the offspring population for the $t^{th}$ generation of the algorithm.

\begin{center}
\begin{tabular}{ll}
\textbf{Begin} & \\
\textbf{Combine parent ($P$) and offspring ($Q$) populations to form a combined population} & \\
$\mathbf{R}_t = P_t \cup Q_t$. Perform a non-dominated sorting to $\mathbf{R}_t$ and identify different fronts: & \\
$\mathbf{F}_i = (1, 2, 3...n)$ & \\
Set new population $\mathbf{P}_{t+1} = \Phi$. Set a counter $i = 1$. & \\
Repeat $\mathbf{P}_{t+1} = \mathbf{P}_{t+1} \cup \mathbf{F}_i$ & \\
$i = i + 1$ & \\
Until $|\mathbf{P}_{t+1}| + |\mathbf{F}_i| < N$ & \\
Perform the Crowding-sort ($|\mathbf{F}_i| < c$) and & \\
Include the most widely spread $(N - |\mathbf{P}_{t+1}|)$ solutions by using the crowding distance & \\
values in the sorted $\mathbf{F}_i$ to $\mathbf{P}_{t+1}$ & \\
\textbf{Repeat Create offspring population $Q_{t+1}$ from $P_{t+1}$ by using}, & \\
Crowded tournament selection & \\
Crossover & \\
Mutation & \\
Perform non dominated sort & \\
Until termination criteria is met & \\
\textbf{End} & \\
\end{tabular}
\end{center}

\textit{Pseudo-code for the NSGA-II algorithm (Deb et al., 2002).}

The \textit{gamultiobj} solver generates a set of Pareto optima solutions based on multi-objective minimization and linear constraints based on control parameter ranges. The multi-objective genetic
algorithm works on a population (set of points in the design space) using a set of operators applied to the population. The algorithm favours individuals with better fitness value (rank) as well as those that can help increase the diversity of the population even if they have a lower fitness value. This is achieved by controlling elite members of the population as the algorithm progresses and is crucial to maintain diversity of the population for convergence to an optimal Pareto front. Two function, (the ParetoFraction and DistanceFcn) are used to control the elitism in the solver used in this research. The Pareto fraction option limits the number of individuals on the Pareto front (elite members) and the distance function helps to maintain diversity on a front by favouring individuals that are relatively far away from each other.

The next generation is computed using a non-dominated rank and a distance measure of individual solutions in the current generation. The regression models are used to formulate a minimization objective function and the solver transforms that measure of performance into an allocation of reproductive opportunities using the fitness function. The solver identifies combinations of parameter levels that yield superior recovery and upgrade ratio by searching the objective space for non-dominated solutions in the objective space. The optimization solution is a Pareto front consisting of the best combination of recovery and upgrade ratio and the decoded parameter level combinations.

4.3.6 Validation and iterations
Experimental CVD tests are performed for the predicted optimum parameter levels in order to validate the optimization solution. Repeat runs are performed to check for experimental and random error. If validation shows that the predicted optimum is inferior to the statistically designed experimental results, then the regression models are modified and optimization repeated until an improvement in metallurgical performance is predicted and validated. If there is no improvement, then the Pareto optimum results should be the same as the experimentally determined boundary line. If ore characteristics change significantly then more experimental data has to be collected and the ANN retrained. The iterative nature of the NNREGA approach allows for continuous improvement.

4.4 Summary
Conceptual analysis showed that concentrate grade is more sensitive than upgrade ratio to feed grade variation. Fluctuation in the composition of gravity recoverable gold bearing sulphides
has potential to render optimization tests futile, when improvement in metallurgical performance as a result of changes in ore characteristics is confused with the effect of control variables. Tests conducted on synthetic quartz magnetite ore confirmed that a decrease in CVD upgrading with increasing bowl speed is overshadowed by increase in feed grade, whilst for upgrade ratio the decrease in performance can be clearly observed despite the change in grade. Therefore, for purposes of measuring the effect of machine parameters on performance, upgrade ratio is more reliable especially when feed grade increases whilst tailing grade remains constant.

The strategic experimental design and ANN simulation used in the \textit{NNREGA} approach reduces the number of experimental tests required for locating the process optima, cutting down on both the time and capital requirements. The approach allows for simultaneous optimization of grade and recovery, and the optimization solution is not a single optimum point, but rather a set of control parameter levels yielding non-dominated combinations of recovery and grade or upgrade ratio. This exploitation of the grade versus recovery relationship in mineral processing is novel, and allows for plant optimization separate from metal economics. The potential to integrate \textit{NNREGA} as an optimization module in the CVD programmable logic control (PLC) is an essential step towards effective plant control.

Two main challenges for the \textit{NNREGA} approach to optimization are: the use of a model of a model, which tends to compound error propagation, and use of models to extrapolate. The error propagation problem is resolved by the fact that ANN models tend to give very good predictions and the variation between ANN models and experimental data is attributed to experimental random error such that ANN simulated data yields a better prediction of the effect of variation in control variables. Therefore the parametric models obtained from simulated data are expected to better represent the underlying trends in output due to variation in regressor levels. The extrapolation employed in NNREGA although it lowers the confidence level, it is an acceptable practice since the levels of the variables jointly define the region containing the data as characteristic of multiple regression (Montgomery & Runger, 2002). It has been proved in the past that ANN models are superior at prediction than classical parametric models. However, parametric models provide mathematical relationships between control variables and response, which help in enhancing process understanding. By combining ANN and regression, better predicting models can be generated, whilst providing an understanding on the relationship between metallurgical response and the control variables. For an operating mine, the use of ANN simulation allows for
operation data to be used both for assessing performance and improve process understanding. When the ore properties vary, different neural networks have to be trained and used for simulation. Although designed for the CVD, NNREGA can be used for optimization of any mineral processing unit process with multiple interacting variables.
Chapter 5: Testing NNREGA CVD performance optimization at Myra Falls

5.1 Introduction

Myra Falls mine lies in the Myra Valley between Mt. Phillips and Mt. Myra located in Strathcona provincial park, Vancouver Island, British Columbia. James Cross and Associates originally staked lynx and Price Mine claims in 1918, whilst the Paramount Mining Company held the Myra Mine claims. In 1959, the Reynolds Syndicate acquired and consolidated all the claims and then sold to the Western Mines Ltd. in 1961. Boliden Limited acquired the mine in 1998 followed by Breakwaters Resources in 2004 and lastly by Nyrstar in August 2011 through acquisition of Breakwaters.

The Myra Falls deposits consist of volcanogenic massive sulphide composed of a diverse collection of mineralized bodies including polymetallic massive sulphides, polymetallic disseminated sulphides, zoned pyritic massive sulphides and stringer sulphide zones. The ore comes from three main sources: the Lynx–Myra-Price system which is fundamentally a sedimentary massive sulphide; the H-W system which is also a massive sulphide; and the Battle-Gap, also a massive sulphide but with significant quantities of sphalerite and tennantite/bornite, and variable amounts of pyrite. The H-W ore-body averages 75 % pyrite whilst the Lynx-Myra-Price ore averages 15 % pyrite. Robinson et al (1996) distinguished two ore bodies a pyritic massive sulphide containing pyrite, sphalerite, chalcopyrite, bornite, tennantite and a baritic massive sulphide containing sphalerite, barite, pyrite, quarts, galena, chalcopryite and tennantite. The principal gold carrier is electrum with 22 to 30 % silver and is associated with bornite rich ores and intergrown with galena and chalcocite. Grain size of the electrum ranges from 50 to 2 microns. The finer fractions are enclosed in tetrahedrite and tennantite, associated with sphalerite and pyrite. Low gold recovery by flotation can be attributed to pyrite rejection to tails. The gangue minerals are primarily pyrite with some barite, quartz and pyrrhotite (Jones et al., 2005; Robinson et al., 1996; Juras 1987; Barrett et al.; Yeomans at al., 2006).

Active mining dates back to 1966 initially with the Lynx open pit mine followed by underground operations: Myra mine in 1969, H-W Mine in 1979 and Battle and Gap in 1996. The concentrator was initially designed for a capacity of 950 tons per day and discovery of the H-W massive sulphide deposit prompted expansion in milling infrastructure to a capacity of initially 2,700 and then to the current capacity of 3,600-4,000 tons per day. Prior to installation of a gravity
circuit, gold recovery was reported at 50% (Ounpuu and Claire, 1992) with typical gold losses of 40,000 Oz/year. Installation of a gravity circuit increased the overall gold recovery by 3% by recovering 5% of the gold in the grinding circuit using Knelson concentrators. Optimization of the gravity circuit increased gravity recovery from 5 to 15% with an overall improvement in gold recovery of 5% (Yeomans et al., 2006). Although plant optimization increased gold recovery, approximately 45-55% gold is still being lost to the tails, accounting to approximately 13,600 Oz/year (based on 2012 annual production data), which equates to 21.1 million USD losses annually in today’s (April 2013) market rates. The CVD has proven capability of recovering middlings from flotation tailings (Klein et al., 2010) and can potentially benefit the operation by scavenging gold from plant tailings. In this research, the CVD was retrofitted on nine processing streams at Myra Falls and its potential benefits assessed.

The erratic occurrence of particulate gold (Clifton, 1969) poses challenges in obtaining statistically meaningful gold assays from reasonably sized samples (Koppalkar, 2009). Gold nugget effect poses sampling problems especially for streams containing coarse, free gold particles and sampling repeatability and accuracy are difficult to achieve. Laplante and his students suggested a procedure to reduce errors which involves screening the plant concentrate product prior to assaying and further upgrading the tails using a laboratory Knelson MD3 unit then sizing both the MD3 concentrate and cut samples obtained from the tails. The gold grade and recovery is obtained by mass balancing assay results (Laplante and Shu 1992; Laplante et al., 1994; Koppalkar 2009). Whilst this procedure reduces the sampling error in gold assays, the total number of samples increases astronomically with number of tests performed, which becomes counterproductive when aiming to reduce the cost of optimizing a plant. Exploiting gold-sulphide mineral associations can offer an alternative to gold sampling especially for the CVD, which is a heavy mineral concentrator, by using base metal minerals as gold indicators.

Klein et al (2010) showed that the CVD is capable of upgrading coarse middlings. Thus by retrofitting the CVD to flotation tailings, coarse primary grinding can be used and the un-liberated gold sulphides recovered and re-circulated for further liberation with potential to increase plant recovery (by reducing generation of non-GRG fines caused by over grinding) whilst reducing milling energy consumption. In this research, out of the nine processing streams tested at Myra Falls, the final tailings (flotation tailings) stream was selected for testing the optimization approach for both pilot and full-scale machines. The choice was based on uniformity in gold grade and
minimum interference with the plant operations. A key consideration when operating the CVD is the fluidization water requirements, when operated over a long period is capable of offsetting the plant water balance. At the Myra Falls plant, gold reporting to the final tailings would have evaded the batch Knelson concentrators in the primary grinding circuit and copper regrind circuit. This is attributed to either in-efficiency in cyclone classification, over grinding or inefficiency in batch Knelson concentration. The gold would have also evaded flotation, which could be attributed to surface tarnishing or un-liberated gold associated with pyrite, since pyrite is rejected in the flotation of copper and zinc. This chapter presents pilot and full-scale CVD optimization results using the NNREGA optimization approach for tuning the control variables in order to maximize metallurgical performance.

5.2 Myra Falls circuit description

The Myra Falls plant was the first mine to install two fully automated Knelson concentrators (CD30), which were decommissioned after 15 years of service and replaced by the current XD30 units. At present, the mill operates two centrifugal batch Knelson XD30 concentrators in parallel to recover free gold from the cyclone underflow in the primary grinding circuit (consisting of open rod milling and closed ball milling) and a Knelson CD 12 in the copper regrind circuit. Figure 5.1 is a schematic of the Myra Falls plant showing the 9 processing streams where pilot scale tests were conducted and the NNREGA approach tested including: XD30 feed, cyclone overflow, copper rougher tails, copper concentrates, copper cleaner tails, lead concentrate, zinc concentrate, flotation (final) tail and zinc feed. Only flotation tails results are presented in this thesis.
The mine has a 270 tph crushing circuit (not shown in the figure), which consist of a primary jaw crusher for the Lynx ore. Ore from the H-W Mine is crushed and carried by a conveyor belt to the mill. Primary crushed ore is fed into a 3,600 tons coarse ore bin prior to screening by a 152.4 cm x 365.8 cm double deck screen with a 19 mm x 51 mm. The undersize go straight to two 3,600 tons fine ore bins. The oversize is crushed in a secondary standard Symons cone crusher in open circuit and the product goes to a single deck 243.8 cm x 487.7 cm with 16 mm x 28 mm apertures Which is in closed circuit with a tertiary Symons short head cone crusher. The fine fraction goes to the fine ore bins.

From the fine ore bin ore is fed to the rod mills and water is added to attain a pulp density between 78-80 %. The milling circuit consists of two parallel open rod mill-closed ball mill circuits with Krebs cyclones for classification. The rod mill discharge and ball mill discharge is fed to the pump box before classification by the cyclones. Cyclone underflow has a pulp density of 80-85 % solids and is fed to the ball mill whilst the cyclone overflow with a pulp density of 42 % goes to flotation. Targeted grind size is 75-80 % passing 75 µm and the ore has an average work index of 13.4 kwh/ton.

Two Knelson XD30 concentrators treat about 45 tph of the re-circulating load in the primary grinding circuit. Prior to decommissioning, reducing cycle time for CD30 machines from...
6 to 1 hour was found to increase gold recovery by 5%. In 2006, a Deister table was installed to replace the secondary treatment of gravity concentrates by a centrifugal concentrator and a Knelson CD 12 unit was installed in the copper regrind circuit.

The Myra Falls flotation circuit essentially recovers base metals by differential flotation, recovering copper first followed by lead and lastly zinc. Galena and sphalerite are depressed in the grinding circuit and pH is adjusted by addition of lime. Lead is depressed by dextrin and monophosphate whilst zinc is depressed by zinc sulphate. Although, soda ash would have been a better pH modifier, the plant uses lime, known to inhibit flotation of free gold and may account for the liberated gold not recovered by the flotation circuit. Copper flotation uses a combination of selective collectors (Cytec Aero 5100 and 3477) that are good for both copper and gold and MIBC as frother. Copper rougher and scavenger concentrates undergo further liberation in the copper regrinding circuit where additional lead and zinc depressants are added. After flotation of copper, galena is activated by addition of sulphur dioxide, which has a depressive effect on sphalerite and pyrite and additional collector (Cytec Aero 3477) is added. The pH of the lead tailings is adjusted to between 10.5 and 11 and sphalerite is activated by addition of copper sulphate. The rougher and scavenger concentrates undergo re-grinding before a cleaning stage. Cleaner scavenger concentrates report to re-grinding whilst the tails join the scavenger tailings to constitute the final tailings (also referred to as zinc tailings).

The gravity circuit recovers about 5-15% of the gold with close to 50% deported to the flotation concentrates. Gold losses to tailings are about 45-55% of the gold in the ore. Diagnostic leaching showed that 39.6% of the gold to tailings is accessible to cyanide hence could either be liberated GRG and non-GRG or exposed and attached to either sulphides or gangue, 21.2% is associated with galena, 10.6% with pyrite and copper sulphides, 2.9% with sphalerite and tetrahedrite and 25.8% with silicates. Gold recovered by gravity has the highest payment, followed by gold in copper and lead concentrates. The gold deported to zinc concentrates has the lowest payment and in some cases no payment. It is therefore desirable to maximize gold recovery to either gravity or copper concentrates.

5.3 Characterization of Myra Falls flotation tails

Characterization of gravity recoverability of the final flotation tails at Myra Falls, in Chapter 3 of this thesis, showed both sulphides and gold in the final tails exhibit inhibited gravity recoverability. Gold in the final tails exist both as liberated particles and middlings associated with
sulphides. And the gravity amenability testing results indicate potential to upgrade gold to above plant feed grade at a recovery above 20%. Rietveld refinement results for XRD of Myra Falls final tailings showed that pyrite accounts for 97% of total iron content and 95% of total sulphides and is therefore a good indicator of pyrite, and pyrite is a good indicator of base metal sulphides. Thus, iron is an acceptable indicator for evaluating sulphides recovery from the flotation tailings using the CVD.

Typical composition of the Myra Falls flotation tailings is shown in Table 5.1. The gold tailings grade of 0.7 g/t accounts for approximately 50% of the gold in the plant feed, which is lost to the tailings. The average pulp density for the stream was 20% solid.

**Table 5.1: Typical metal composition in final tailing at Myra Falls.**

<table>
<thead>
<tr>
<th>Metal of interest</th>
<th>Au (g/t)</th>
<th>Ag (g/t)</th>
<th>Cu (%)</th>
<th>Pb (%)</th>
<th>Zn (%)</th>
<th>Fe (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Composition</td>
<td>0.7</td>
<td>12.4</td>
<td>0.1</td>
<td>0.2</td>
<td>0.7</td>
<td>5.4</td>
</tr>
</tbody>
</table>

The valuable minerals evading flotation may be locked in either pyrite or silicate gangue. Since the fine gold in the ore at Myra Falls is associated with pyrite and sphalerite, depressing of pyrite in flotation of base metal sulphides can account for significant gold losses to flotation tails. Whilst the use of Aero 5100 promotes recovery of liberated gold, it does depress iron sulphides and therefore gold associated with pyrite. In addition the use of lime as a pH modifier is known to depress gold, thus part of the liberated gold can also be lost as a result of poor reagent selection. Figure 5.2 shows weight and gold distribution by size in the flotation tails.
Gold distribution follows the weight distribution trend. Since gold exist as electrum at Myra Falls, the presence of silver is known to reduce gold recovery by flotation and the higher the silver value the higher the chances that the electrum particles will evade flotation. When viewed under an optical microscope, Myra Falls gold particles have tarnished surfaces, and are considerably flattened and rolled attributed to deformation by overgrinding. During ball milling, iron compounds can precipitates on the gold surfaces forming a coat. According to Bulatovic (1997), flotation recovery of flattened and coated gold particles is erratic and weak even with high collector. Thus the fine gold lost to tailings maybe attributed to high silver electrum, tarnished, flattened or rolled liberated gold or un-liberated gold.

Sampling errors resulting from erratic gold distribution can offset the variation due to changing control variable levels and render an optimization campaign futile. Sulphides are relatively abundant and easier to assay. When gold is associated with base metal sulphides, the sulphides can be used as a proxy for gold recovery. Since the CVD recovers both gold and heavy minerals (Ghaffari, 2004), and gold in Myra Falls flotation tailings is associated with pyrite, iron is used as a gold proxy for optimization purposes.

Figure 5.3 is a plot of the variation of gold and iron feed grade versus test number, to demonstrate the variability of gold assays compared to sulphides, showing that gold assays are more erratic than sulphides. However, since most of the gravity recoverable gold in the final tails is locked in sulphides as middlings, gold assay results are expected to be more repeatable than in
the grinding circuit. There is still some variation in the iron feed grade to warrant the use of upgrade ratio instead of concentrate grade as a performance measure for purposes of optimization.

![Figure 5.3: Variation of gold and iron grades in the final tailings stream.](image)

### 5.3.1 Prediction of mineral association by correlating metal grades

Correlating metal assays can provide inference into possible mineral associations. A good correlation of grades indicates possible mineral association. By plotting lead against iron assays in Figure 5.4, it is evident that there are two types of mineralization, one with high Pb/Fe ratio and the other with a lower ratio. The high iron mineralization accounts for pyritic massive sulphide, with characteristic high sphalerite, pyrite and chalcopyrite, whilst the low iron mineralization corresponds to the baritic massive sulphides, with high galena. These findings are in agreement with mineralogical studies done on Myra Falls ore body (Robinson et al., 1996).
In order to assess mineral associations, CVD6 test results were split according to mineralization, and iron grade was plotted against the other base metals and gold grades for CVD feed, concentrate and tailings. Figure 5.5(a) shows no significant association between pyrite and the other base metal sulphides for pyritic massive sulphides, (b) shows significant association between pyrite and gold and base metal sulphides except for copper sulphides for baritic massive sulphides, (c) shows two gold outliers indicating free gold was captured by the CVD and, (d) shows that gold/pyrite association in pyritic massive sulphides is better observed when the outliers are removed.

The results show that whilst pyrite association with base metals is dependent on ore type, with baritic massive sulphide ore showing better association of base metal sulphides, gold association with pyrite in the flotation tails is independent of the ore type. Therefore, iron is a good proxy for gold.
Figure 5.5: Plots of Fe grade against base metals and gold grades in CVD feed, concentrate and tailings at Myra Falls.

Figure 5.6 shows similar plots for CVD concentrate results separated from feed and tailings grade for the baritic sulphide ore. The results show that for the baritic sulphide ore, pyrite/galena and pyrite/gold association is only significant in the CVD concentrate, indicating that the gold and base metal sulphides recoverable by the CVD from flotation tails are mainly composite sulphide particles. Iron and therefore pyrite is a good indicator for the base metals and gold recovered by the CVD from flotation tails.
Figure 5.6: Plots of Fe grade against lead and gold grades in CVD concentrate (a) and (c) and compares with association in CVD feed and tails for baritic sulphide ore (b) and (c).

Figure 5.7 shows optical microscopy results obtained for a Myra Falls flotation tails, CVD concentrate, which shows that most of the base metal sulphides recovered by gravity are un-liberated composite particles. Since the CVD recovers un-liberated middlings, both base metals and precious metal bearing sulphides (Klein et al., 2010), and no gold bearing gangue was observed under the optical microscope, it is reasonable to assume that the gold recovered by the CVD from Myra Falls final tails is mostly associated sulphides and in particular pyrite. Most of the
free gold contained in the flotation tailings is too fine to be recovered having been rendered non-recoverable by over grinding in the primary grinding circuit and the regrind circuit.

Figure 5.7: CVD concentrate from Myra Falls flotation tails showing composite particles of pyrite and galena (white), chalcopyrite (yellow) and sphalerite (grey)

Therefore in this research iron recovery was used as a CVD recovery indicator for gold bearing sulphides, and comparison of the iron and gold results is made based on pilot scale (CVD6 and full scale CVD42) optimization using the NNREGA procedure.

5.4 Experimental methodology

A pilot scale CVD6 and a full scale CVD42 machine were used for the experimental tests. Figure 5.8 shows the machines and a conceptual diagram showing how the CVDs were retrofitted to the existing processing circuit in order to perform the tests. The mechanism of separation, main features and operating variables for the CVD are described in section 2.2 of this thesis.
The CVD6 is the smallest of the CVD series of machines. It consists of a 6-inch diameter fluidised bowl mounted on a rotor assembly. According to data obtained from manufacturer, its feed capacity ranges between 0.5 - 2 tonnes/h and can handle a volumetric flow rate of 4 m³/h at a feed density ranging between 0 - 50%. The recommended maximum feed size is 1.7 mm. Fluidisation flow rate range between 4 – 8 gal/min and it can be operated at centrifugal forces between 5 - 100g. Like all CVDs, feed is introduced into the rotating bowls through a central stationary feed pipe. A super velocity ring positioned above the concentrating ring splits the partly stratified bed of particles into a heavy fraction that enters the fluidised concentrate ring and a light
fraction that overflows the bowl and is collected into a tailings launder. A total of 8, 11.1 mm diameter air actuated pinch valves located 98.4 mm apart around the concentrate ring allows for continuous concentrate discharge to a concentrate launder. Typical pinch valve open and close durations range from 10 to 60 cycles/min.

The CVD42, which was used for the full-scale tests, is the second largest CVD machine. It can handle 40 - 120 tonnes/h solids and maximum volumetric throughput is 250 m³/h at 0 - 50% feed density. The recommended maximum feed size is 1.7 mm. Fluidisation flow rate range between 40 – 100 gal/min and it can be operated at centrifugal forces between 30 – 90 g. The mechanism by which feed is introduced into the machine and particle mobility resembles that of the pilot scale CVD. The CVD42 has a total of 24, 7.9 mm diameter air actuated pinch valves located 177.8 mm apart around the concentrate ring. These pinch valves allows for continuous concentrate discharge to a concentrate launder. Typical pinch valve open and close time duration is in the same range as the pilot scale unit.

The performance of the CVD6 and CVD42 machines was determined by varying operating conditions according to the circumscribed central composite design experimental matrix described in chapter 4. A three-way stainless steel ball valve was fitted to regulate the feed flow rate. For the CVD6, feed was bled from the plant centralized on line elemental analyzer sampling point, the pulp was gravity fed to the CVD in order to reduce segregation. There was not much flexibility for machine positioning for the CVD42 due to machine size and safety requirements. The CVD42 was therefore installed next to the grinding circuit and a bleed for the CVD42 was taken from the plant tails prior to thickening. The pulp was first diverted to a reservoir before pumping to the CVD42. Valves mounted on the feed pipe were used to regulate the feed rate by diverting excess pulp to a tailings sump.

For the pilot scale tests the feed stream was sampled by cutting across a downward flowing stream using a sample cutter. The feed rate was measured by collecting timed samples, weighing the samples prior to filtering and drying and then measuring the dried samples. Timed samples of the whole stream were collected for tailings and concentrate products. Sufficient velocity to cause turbulence was maintained during the course of the pilot tests to prevent particle settling. The sampling points for feed, concentrates and tailings are shown in the schematic in Figure 5.8.

For the full-scale machine, the feed rate and concentrate flow rate was measured by diverting the streams into a 200 L barrel and the time taken to fill the barrel to a predetermined
volume (160 L for the feed and 60 L for concentrate) recorded. A Marcy scale was used to measure the pulp density and the results obtained were compared to the plant daily average. The solids specific density used to convert the volumetric flow rate to tonnage was determined by using a pycnometer. The pulp density was verified by comparing the pulp and dry solids weight of samples collected during testing.

McLeavy (2005) determined the effect of varying feed pulp density on CVD6 performance using quartz/magnetite synthetic ore. The results showed pulp density has negligible impact on both concentrate grade and mass pull. Within experimental error there was negligible change in recovery as the pulp density was increased from 25 to 35 %, however, further increase in solids percent drastically reduced the recovery. The best pulp density for the CVD was considered to be around 30 % solids. Since recovery is a product of mass yield and upgrade ratio, the change in recovery as solids percent increases is attributable to a decrease in upgrading. When the pulp density is increased whilst feed rate remains constant, the capacity of the concentrate ring for the heavy fraction can be exceeded, such that the excess heavy fraction in the feed is rejected to the tailings. The actual value of the peak pulp density should therefore vary with changes in feed rate. Since there is limited flexibility for adjusting pulp density in an operating plant, in this research, the pulp density was measured and any variation during the test period noted. Feed rate was maintained constant and any variation noted during the test period.

To avoid contamination, sample loss and incomplete drying samples were weighed, to account for the pulp density, then allowed to decant for an hour and the excess water was removed. The residual pulp was filtered and the filtered cake was weighed and then dried in the oven for 8 hours at 60 degrees Celsius to ensure all the moisture was removed. The dried sample was weighed, rolled to break lumps and riffled. To avoid contamination during sample preparation all equipment was cleaned prior to use and once the samples were dried, they were kept in sealed sample bags to prevent dust contamination and dust losses. Care was taken during transfer of samples for assaying to avoid spillage. All samples were assayed at the Myra Falls assaying laboratory for base metals, silver and gold. The assay results and the flow rates were used for metallurgical balancing.

5.5 **NNREGA pilot scale optimization results**

CVD optimization results for iron and gold are presented in the following section.
5.5.1 **NNREGA pilot scale testing results for iron as indicator for sulphides**

This section presents the *NNREGA* optimization results for iron as a pyrite indicator and gold bearing base metal sulphides proxy for the CVD6. The objective was to test how applicable the optimization procedure is for tuning the CVD to maximize metallurgical performance.

5.5.1.1 **Statistical experimental results**

Table 5.2 shows experimental results of 17 statistically designed experiments for iron. Consisting of eight $2^3$ factorial experimental runs, 3 centre point repeats and 6 star points to allow further exploration of the design space. Results of the factorial design experiments were used to select the variable levels for the star points. Low pinch valve open duration and high pinch valve closed duration increased iron upgrading, whilst high pinch valve open duration and low pinch valve closed duration increased recovery due to increase in mass yield as a result of reduced particle residence time. Increasing the bowl speed increased iron upgrading this is attributable to the increased rate of settling due to the centrifugal force field. Iron recovery ranged from 3.3 to 30.4 % whilst upgrade ratio ranged from 1 to 3.4. Due to variation in iron feed grade in the course of testing, upgrade ratio and iron recovery were selected as performance measures for optimization purposes.
Table 5.2: Statistical design experiments results for iron.

<table>
<thead>
<tr>
<th>PVO (s)</th>
<th>PVC (s)</th>
<th>BS (g)</th>
<th>Feed rate (tph)</th>
<th>Feed grade (%)</th>
<th>Concentrate grade (%)</th>
<th>Tail grade (%)</th>
<th>Recovery (%)</th>
<th>Upgrade ratio</th>
<th>Mass yield (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>5</td>
<td>20</td>
<td>0.8</td>
<td>5.2</td>
<td>7.8</td>
<td>5.1</td>
<td>6.4</td>
<td>1.5</td>
<td>4.3</td>
</tr>
<tr>
<td>0.4</td>
<td>5</td>
<td>20</td>
<td>0.5</td>
<td>4.9</td>
<td>5.1</td>
<td>4.8</td>
<td>30.4</td>
<td>1.0</td>
<td>29.2</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>20</td>
<td>0.6</td>
<td>5.1</td>
<td>6.4</td>
<td>5.0</td>
<td>4.6</td>
<td>1.3</td>
<td>3.6</td>
</tr>
<tr>
<td>0.3</td>
<td>10</td>
<td>30</td>
<td>0.9</td>
<td>5.1</td>
<td>5.9</td>
<td>5.0</td>
<td>15.0</td>
<td>1.1</td>
<td>13.0</td>
</tr>
<tr>
<td>0.3</td>
<td>10</td>
<td>30</td>
<td>0.8</td>
<td>5.3</td>
<td>6.6</td>
<td>5.0</td>
<td>19.4</td>
<td>1.2</td>
<td>15.5</td>
</tr>
<tr>
<td>0.2</td>
<td>5</td>
<td>40</td>
<td>0.7</td>
<td>5.7</td>
<td>10.8</td>
<td>5.1</td>
<td>18.1</td>
<td>1.9</td>
<td>9.5</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>40</td>
<td>0.9</td>
<td>5.7</td>
<td>15.3</td>
<td>5.4</td>
<td>7.1</td>
<td>2.7</td>
<td>2.6</td>
</tr>
<tr>
<td>0.4</td>
<td>15</td>
<td>40</td>
<td>0.7</td>
<td>5.1</td>
<td>5.1</td>
<td>5.2</td>
<td>23.0</td>
<td>1.0</td>
<td>23.2</td>
</tr>
<tr>
<td>0.3</td>
<td>10</td>
<td>30</td>
<td>0.7</td>
<td>5.4</td>
<td>6.7</td>
<td>5.2</td>
<td>19.4</td>
<td>1.2</td>
<td>15.8</td>
</tr>
<tr>
<td>0.3</td>
<td>15</td>
<td>60</td>
<td>0.7</td>
<td>5.6</td>
<td>15.2</td>
<td>5.0</td>
<td>15.7</td>
<td>2.7</td>
<td>5.7</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>60</td>
<td>0.7</td>
<td>5.5</td>
<td>15.0</td>
<td>5.2</td>
<td>9.5</td>
<td>2.7</td>
<td>3.5</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>90</td>
<td>0.9</td>
<td>6.9</td>
<td>33.5</td>
<td>5.4</td>
<td>25.9</td>
<td>4.9</td>
<td>5.3</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>60</td>
<td>0.6</td>
<td>7.5</td>
<td>25.7</td>
<td>6.6</td>
<td>16.7</td>
<td>3.4</td>
<td>4.9</td>
</tr>
<tr>
<td>0.2</td>
<td>18</td>
<td>60</td>
<td>0.5</td>
<td>7.6</td>
<td>24.2</td>
<td>6.8</td>
<td>13.5</td>
<td>3.2</td>
<td>4.2</td>
</tr>
<tr>
<td>0.25</td>
<td>20</td>
<td>60</td>
<td>0.4</td>
<td>7.1</td>
<td>15.1</td>
<td>6.3</td>
<td>19.1</td>
<td>2.1</td>
<td>9.0</td>
</tr>
<tr>
<td>0.3</td>
<td>30</td>
<td>40</td>
<td>0.4</td>
<td>6.8</td>
<td>13.6</td>
<td>6.2</td>
<td>15.5</td>
<td>2.0</td>
<td>7.7</td>
</tr>
<tr>
<td>0.2</td>
<td>30</td>
<td>60</td>
<td>0.5</td>
<td>7.5</td>
<td>25.8</td>
<td>7.0</td>
<td>9.6</td>
<td>3.4</td>
<td>2.8</td>
</tr>
</tbody>
</table>

5.5.1.2 Artificial neural network training results

The statistical design experiments data was used as input for training a feed forward back propagation neural network using a commercial Matlab ANN toolbox software version 7.10. The Matlab neural network toolbox convention, where the output layer is not counted in the hidden layer was used throughout this research. The Levenberg-Marquardt algorithm with an early stopping procedure, which monitors error variation during training, was used in order to avoid over fitting. The algorithm is the fastest method of training moderate sized networks. Data was randomly divided into three subsets: 60 % training, 20 % validation and 20 % testing. The training
set was used for computing the error gradient in and updating the network weights and biases. The validation set was used to avoid network overfitting by monitoring the validation error during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to overfit data, the error on the validation set typically begins to rise. When the validation error increases for six iterations, training was stopped, and the weights and biases at the minimum of the validation error were retained. The testing set determines how good the model is at estimating output when presented with data not used during training.

Figure 5.9 shows a screenshot for ANN training showing variation of training, validation and testing errors for a recovery network. It shows that the network started over fitting after the 4th epoch, when the validation error and testing errors started to increase whilst the training error continued to decrease. The best performance was therefore MSE = 0.16 at epoch 4 as indicated by the intersection of the dotted lines. A [3 8 1] network yielded the best training results for Recovery.

![Figure 5.9: Screenshot of parity plot between epoch and mean square error for training of a recovery network. Showing the training error in (blue), validation error in (green), and testing error in (red).]

By varying the number of hidden neurons and monitoring network performance, a [3 5 1] network yielded the best performance for upgrade ratio. Network training stopped when the validation error increased for six epochs, which occurred at iteration 18, the best validation error occurred at epoch 12.
Figure 5.10 shows ANN prediction results for iron recovery and upgrade ratio, the mean for the centre repeats was calculated and used instead of all three points. The ANN models show good prediction with high correlation coefficients, 0.95 and 0.95 recovery and upgrade ratio are respectively.

![Figure 5.10: Scatter plot for ANN models (a) recovery and (b) upgrade ratio showing good correlation.](image)

To demonstrate that the ANN models have superior prediction, regression models of varying order up to cubic with interaction were fitted on the experimental data and results of the best model was compared to the ANN results. Table 5.3 gives a comparison of the models and shows that ANN models give better prediction and are therefore preferred to regression models derived from experimental data.

**Table 5.3: Coefficient of determination for ANN and regression models showing ANN has better prediction.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Upgrade ratio</th>
<th>Recovery</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Regression</td>
<td>0.89</td>
<td>0.89</td>
</tr>
</tbody>
</table>

In order to demonstrate data smoothing by ANN, regression models based on experimental data were compared to those based on ANN simulation data. ANN simulation data for recovery and upgrade ratio was generated using the trained networks. Figure 5.11 shows results obtained from fitting regression models of different orders on both the experimental data and simulation
data. Comparison of the prediction accuracy of the models is based on the coefficient of
determination. The results show that it is easier to fit regression models on ANN simulated data
than on experimental data, showing how ANN simulation smoothen experimental data. Models
based on simulated data are consistently superior to models based on experimental data.

Figure 5.11: Comparison of regression models based on ANN simulated and experimental data for models of
increasing order (1) linear and interactions (2) full quadratic (3) squared and interactions (4) full cubic.

5.5.1.3 Regression modeling

Tables 5.4 and 5.5 show stepwise regression modeling and analysis of variance (ANOVA)
results for the recovery model. A second order model with third order interactions had the best fit
for recovery.

Table 5.4: Recovery model coefficients

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>P value</th>
<th>Std Error</th>
<th>-95%</th>
<th>95%</th>
<th>t Stat</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_0$</td>
<td>17.24</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>16.8</td>
<td>17.6</td>
<td>96.5</td>
</tr>
<tr>
<td>$b_1$</td>
<td>6.908</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>6.5</td>
<td>7.3</td>
<td>38.6</td>
</tr>
<tr>
<td>$b_2$</td>
<td>-4.716</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>-5.1</td>
<td>-4.3</td>
<td>-24.7</td>
</tr>
<tr>
<td>$b_3$</td>
<td>-7.253</td>
<td>&lt; 0.001</td>
<td>0.4</td>
<td>-8.2</td>
<td>-6.3</td>
<td>-16.8</td>
</tr>
<tr>
<td>$b_4$</td>
<td>6.741</td>
<td>&lt; 0.001</td>
<td>0.5</td>
<td>5.6</td>
<td>7.9</td>
<td>13.5</td>
</tr>
<tr>
<td>$b_5$</td>
<td>-1.641</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>-2.1</td>
<td>-1.2</td>
<td>-7.7</td>
</tr>
<tr>
<td>$b_6$</td>
<td>-1.373</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>-1.9</td>
<td>-0.8</td>
<td>-5.7</td>
</tr>
</tbody>
</table>

$\text{Recovery} = b_0 + b_1 x_1 + b_2 x_1 x_3 + b_3 x_1 x_2^2 + b_4 x_1 x_2 x_3 + b_5 x_2 + b_6 x_1^2$  

5.1
where:  
\[ x_1 = \text{coded value of pinch valve open duration} \]
\[ x_2 = \text{coded value of pinch valve closed duration} \]
\[ x_3 = \text{coded value of bowl speed} \]

The significance of each parameter and the associated interaction effects were determined by testing the hypothesis that the corresponding coefficients in the model are zero using both Student’s t-test and p-values, shown in Table 5.4. A high t-value and low p-value shows a significant coefficient. The p-values < 0.001 for all coefficients therefore there is very strong evidence against the null hypothesis in favour of the alternative, implying that the variation in recovery is more likely to be a result of the effect of changes in pinch valve timing and bowl speed than random error. For the selected model, the variance inflation factor (VIF) < 10 for all coefficients showing low multicollinearity among regressors.

<table>
<thead>
<tr>
<th>Sources of variation</th>
<th>Sum of squares</th>
<th>Degrees of freedom</th>
<th>Mean square</th>
<th>F value</th>
<th>Prob (P) &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>528.74</td>
<td>6</td>
<td>88.12</td>
<td>644.02</td>
<td>2.4 x 10^{-12}</td>
</tr>
<tr>
<td>Residual</td>
<td>1.368</td>
<td>10</td>
<td>0.137</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>530.11</td>
<td>16</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R^2 = 0.997, R = 0.999, Adjusted R^2 = 0.996

The recovery model passed both the significance test and lack of fit tests. A low probability value (P_{model} > F = 2.49 x 10^{-12}) using the fisher F-test demonstrates that the model is highly significant (Adinarayana & Ellaiah, 2002; Cochran & Cox, 1957). An R^2 = 0.997 and R^2_{adj} = 0.996 show good correlation with no over fitting, implying that almost all the variation in recovery is fully described by the regression model.

The pinch valve open duration (PVO) had the most significant contribution to variation in iron recovery. This is because increasing PVO increases the mass yield and therefore recovery. The most significant interaction effects were (BS x PVO, PVO x PVC x PVC and BS x PVO x PVC). Increasing PVO and PVO x PVC x BS the three factor interactions increased the recovery. Increasing all three variables, increased iron recovery due to the coupled effect of increased mass yield, as a result of increasing bowl speed and pinch valve open duration, and increase in upgrade ratio as a result of increasing pinch valve closed duration.
Stepwise regression modeling for upgrade ratio yielded a second order model with interactions. Table 5.6 shows the upgrade ratio model with the P-values and t-statistics for each coefficient.

Table 5.6: Upgrade ratio model coefficients

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>P value</th>
<th>Std Error</th>
<th>95%</th>
<th>95%</th>
<th>t Stat</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_0$</td>
<td>1.6</td>
<td>&lt; 0.001</td>
<td>0.1</td>
<td>1.4</td>
<td>1.7</td>
<td>19.8</td>
</tr>
<tr>
<td>$b_1$</td>
<td>0.6</td>
<td>&lt; 0.001</td>
<td>0.1</td>
<td>0.4</td>
<td>0.8</td>
<td>7.4</td>
</tr>
<tr>
<td>$b_2$</td>
<td>-0.7</td>
<td>&lt; 0.001</td>
<td>0.1</td>
<td>-0.9</td>
<td>-0.4</td>
<td>6.6</td>
</tr>
<tr>
<td>$b_3$</td>
<td>-0.4</td>
<td>0.01</td>
<td>0.1</td>
<td>-0.6</td>
<td>-0.1</td>
<td>6.6</td>
</tr>
<tr>
<td>$b_4$</td>
<td>0.3</td>
<td>0.04</td>
<td>0.1</td>
<td>0.0</td>
<td>0.6</td>
<td>2.3</td>
</tr>
</tbody>
</table>

Upgrade ratio = $b_0 + b_1x_3 + b_2x_1 + b_3x_1x_3 + b_4x_2^2$

where:

- $x_1$ = coded value of pinch valve open duration
- $x_2$ = coded value of pinch valve closed duration
- $x_3$ = coded value of bowl speed

Table 5.7 shows ANOVA results for the upgrade ratio model. The model passed the significance and lack of fit test with a $R^2 = 0.95$ and $R^2_{adj} = 0.94$ showing good correlation without over-fitting and a low probability value ($P_{model} > F = 7.06 \times 10^{-8}$) showing high significance.

Table 5.7: Analysis of variance (ANOVA) results for upgrade ratio model

<table>
<thead>
<tr>
<th>Sources of variation</th>
<th>Sum of squares</th>
<th>Degree of freedom</th>
<th>Mean square</th>
<th>F-value</th>
<th>Prob (P) &gt;F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>9.371</td>
<td>4</td>
<td>2.34</td>
<td>61.12</td>
<td>7.06 x10^{-8}</td>
</tr>
<tr>
<td>Residual</td>
<td>0.460</td>
<td>12</td>
<td>0.038</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>9.831</td>
<td>16</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = 0.95$, $R= 0.97$, Adjusted $R^2 = 0.94$

The p-value is less than 0.01 for coefficients $b_0$ to $b_2$ showing very strong evidence against the null hypothesis in favour of the alternative, whilst for $b_3$ and $b_4$ the evidence against the null hypothesis is moderate but still significant. VIF is less than 10 for all coefficients, showing low colinearity between the control parameters. Increasing PVC and BS increased upgrade ratio whilst increasing PVO and PVO x PVC interactions decreased upgrade ratio. Increasing PVC increases the degree of upgrading within the concentrate ring, whilst increasing BS increases the extent of upgrading due to differential settling as particles migrate up the bowl. Increasing PVO increases
the proportion of unclassified particles exiting the CVD through the pinch valves thereby diluting the concentrate grade and consequently lowering the upgrade ratio.

5.5.1.4 Formulation of optimization problem

The optimization problem was formulated as a minimization of a vector of objectives \( \mathbf{F}(\mathbf{x}) \), subject to boundary constraints shown below:

Minimize \( \mathbf{F}(\mathbf{x}) = [-R(x_1, x_2, x_3) - \text{Ur}(x_1, x_2, x_3) = [f(1), f(1)] \)

subject to:

\[-1 \leq x_1 \leq 1 \]
\[-1 \leq x_2 \leq 1 \]
\[-1 \leq x_3 \leq 1 \]

where \( x_1 \) is the coded pinch valve open duration, \( x_2 \) is the coded pinch valve closed duration, \( x_3 \) is the coded bowl speed, \( R \) is iron recovery and \( \text{Ur} \) is iron upgrade ratio.

\[ f(1) = -17.24 - 6.908x_1 + 4.716x_1x_3 + 7.253x_1x_2^2 - 6.741x_1x_2x_3 + 1.641x_2 + 1.373x_1^2 \]

\[ f(2) = -1.567 - 0.616x_3 + 0.653x_1 + 0.532x_1x_2 - 0.29x_2^2 \]

But \( f(1) \) and \( f(2) \) are competing objectives; there is no unique solution to \( \mathbf{F}(\mathbf{x}) \) instead, the concept of non-inferiority is used to characterize the objectives. A non-inferior solution is one in which an improvement in one objective requires a degradation of another. This is characteristic of the relationship between concentrate grade (and therefore upgrade ratio) and recovery. Since \( \mathbf{F}(\mathbf{x}) \) maps parameter space into objective function space, optimization involves identifying the non inferior solution (also known as Pareto front) in the objective space using genetic algorithm search techniques as described in chapter 4. Since the Pareto front consists of the non-dominated solution of the population, it defines the optimum grade versus recovery operating line.

5.5.1.5 Optimization results

Figure 5.12 shows the Pareto optimum solutions obtained using the \textit{NNREGA} approach and compares predicted optimum with initial experimental results. The predicted Pareto curve forms an envelop above initial statistical experimental design results showing the optimum grade versus recovery iron curve for the CVD 6. Table 5.8 shows the decoded corresponding variable levels. New experimental data was collected for 4 predicted data points to validate the predicted
Pareto curve, and the results are shown in Figure 5.12 (b), showing good agreement between predicted and experimental data, thus validating the optimization approach.

![Figure 5.12: Pareto optimum solution for iron showing (a) that the predicted optimum results form an envelope above the statistical experimental results, thus predicting improved metallurgical performance, (b) experimental validation of predicted optimum.](image)

The results show that \textit{NNREGA} optimization results envelop the initial statistical experimental results, coinciding with most of the extreme points whilst identifying other non-dominated combinations of upgrade ratio and recovery and the corresponding parameter levels. There is reasonable correlation of the predicted results and experimental validation results in Figure 5.12 (b). Table 5.8 shows the corresponding parameter settings for the predicted Pareto optimum solution. The results show that increasing pinch valve open duration increases recovery whilst lowering the pinch valve open duration increases upgrade ratio at the expense of recovery. Increasing the bowl speed increases the upgrade ratio. Iron and therefore sulphides recovery is maximized by increasing the pinch valve open duration and reducing both bowl speed and pinch valve close time. Whilst reducing pinch valve open duration and increasing both pinch valve closed duration and bowl speed increases upgrade ratio. Comparing gold and iron optimization results, both results show similar trends, but different optimization parameter levels are predicted, which is expected due to the difference in specific density of the targeted species.
Parameter levels yielding best performance for sulphides are not the same as those for gold; this is attributed to differences in separation characteristics between gold and iron based on the difference in specific gravity.

### 5.5.2 NNREGA pilot scale testing results for gold

Iron results in the previous section show the NNREGA procedure can predict optimum CVD metallurgical performance. Due to particle sparsity, gold sampling is complex and assaying is erratic such that an improvement in performance due to tuning parameters can be rendered insignificant due to sampling error. Some modification to test procedure used for iron included using more repeats and more experimental runs in order to better explore the design region. The control parameter range tested is given in Table 5.9. The minimum and maximum for pinch valve durations are limited by the mass yield requirements.

Table 5.9: Control parameter range.

<table>
<thead>
<tr>
<th>Level</th>
<th>PVO (s)</th>
<th>PVC (s)</th>
<th>BS (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>0.2</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.4</td>
<td>15</td>
<td>90</td>
</tr>
</tbody>
</table>

Table 5.10 shows gold experimental results of 30 factorial and circumscribed central composite designed experiments.
5.5.2.1 Statistical experimental results

Table 5.10: Statistical design experiments results for gold.

<table>
<thead>
<tr>
<th>PVO (s)</th>
<th>PVC(s)</th>
<th>BS (g)</th>
<th>Feed rate (tph)</th>
<th>Feed grade (g/t)</th>
<th>Concentrate grade (g/t)</th>
<th>Tail grade (g/t)</th>
<th>Mass yield (%)</th>
<th>Recovery (%)</th>
<th>Upgrade ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>5</td>
<td>20</td>
<td>0.5</td>
<td>0.8</td>
<td>1.5</td>
<td>0.7</td>
<td>4.7</td>
<td>9</td>
<td>1.9</td>
</tr>
<tr>
<td>0.4</td>
<td>5</td>
<td>20</td>
<td>0.6</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>29.2</td>
<td>32.2</td>
<td>1.1</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>20</td>
<td>0.9</td>
<td>0.6</td>
<td>0.7</td>
<td>0.6</td>
<td>3.6</td>
<td>4.3</td>
<td>1.2</td>
</tr>
<tr>
<td>0.3</td>
<td>10</td>
<td>30</td>
<td>0.8</td>
<td>0.5</td>
<td>0.9</td>
<td>0.9</td>
<td>14.6</td>
<td>26.3</td>
<td>1.8</td>
</tr>
<tr>
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<td>10</td>
<td>30</td>
<td>0.7</td>
<td>0.8</td>
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<td>26.0</td>
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<td>2.4</td>
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<td>2.6</td>
<td>5.0</td>
<td>1.9</td>
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<tr>
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<td>0.7</td>
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<td>27.0</td>
<td>1.8</td>
</tr>
<tr>
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<td>0.7</td>
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<td>1.9</td>
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<td>0.6</td>
<td>0.6</td>
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<td>0.7</td>
<td>1.7</td>
<td>0.5</td>
<td>9.5</td>
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<td>2.4</td>
</tr>
<tr>
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<td>0.5</td>
<td>14.6</td>
<td>26.3</td>
<td>1.8</td>
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<tr>
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<td>6.3</td>
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<td>2.4</td>
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<td>2.5</td>
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<td>0.6</td>
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<td>0.5</td>
<td>6.0</td>
<td>11.0</td>
<td>1.8</td>
</tr>
<tr>
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<td>0.7</td>
<td>0.6</td>
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<td>0.6</td>
<td>24.0</td>
<td>24.0</td>
<td>0.9</td>
</tr>
<tr>
<td>0.4</td>
<td>10</td>
<td>40</td>
<td>0.8</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
<td>24.0</td>
<td>24.0</td>
<td>0.8</td>
</tr>
<tr>
<td>0.4</td>
<td>15</td>
<td>30</td>
<td>0.7</td>
<td>0.8</td>
<td>1.1</td>
<td>0.7</td>
<td>15.3</td>
<td>21.0</td>
<td>1.4</td>
</tr>
<tr>
<td>0.2</td>
<td>15</td>
<td>60</td>
<td>0.9</td>
<td>0.7</td>
<td>2.2</td>
<td>0.5</td>
<td>4.0</td>
<td>12.6</td>
<td>3.1</td>
</tr>
</tbody>
</table>

The experimental results show that gold recovery ranges from 4 to 32.2 ± 0.6 % whilst upgrade ratio ranges from 1 to 3.4 ± 0.2. Within a bowl speed range of 20 - 60 g, increasing the bowl speed increased both upgrade ratio and gold recovery. Low pinch valve closed duration yielded superior gold recovery especially for high bowl speeds. For low bowl speeds, low pinch
valve close duration yield better gold upgrading, however this changes with increase in bowl speed, such that at high bowl speeds higher pinch valve closed duration yields higher gold upgrading.

Figure 5.13: The effect of bowl speed and pinch valve closed duration on gold recovery using a CVD6 at Myra Falls.

The broken lines show the error limits.

The results show significant variation in gold feed grade to warrant the use of upgrade ratio for purposes of optimization. Therefore, gold recovery and upgrade ratio were selected as the metallurgical performance measures.

5.5.2.2 Artificial neural network training results

The 30 data points from statistical design experiments were used to train neural networks. The data was randomly divided into three subsets: 20 (~66 %) training and each 5 (~17 %) validation and testing during training. By varying the number of hidden neurons and monitoring network performance a [3 9 1] network, yielded the best performance for upgrade ratio. Network training stopped when the validation error remained constant for four epochs, which occurred at iteration 6. A [3 12 1] network yielded the best training results for recovery. Training stopped when the validation error increased for six iterations, which occurred at iteration 23. The test set and the validation set errors had similar trends and no significant over fitting had occurred by
iteration 17 (where the best validation performance occurred). Comparison of experimental data with ANN predicted data is shown in Figure 5.14. The correlation coefficients between observed and predicted recovery and upgrade ratio are 0.82 and 0.92 respectively. The ANN models predict the output satisfactorily but not as good as, it predicts iron results. The recovery network had a lower coefficient of determination and the plot (a) shows a degree of scatter, attributed to random error in the experimental data due to gold sampling and assaying difficulties. However, ANN models yield better prediction than regression models as shown in Table 5.11.

Table 5.11: Coefficient of determination for ANN and regression models.

<table>
<thead>
<tr>
<th></th>
<th>Upgrade ratio</th>
<th>Recovery</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>0.92</td>
<td>0.82</td>
</tr>
<tr>
<td>Regression</td>
<td>0.79</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Figure 5.14: Scatter plot for ANN models (a) recovery and (b) upgrade ratio.

Figure 5.15 shows results for comparison of regression models based on experimental and simulation data for gold. The difference in prediction is higher for the gold models than iron. This shows that ANN modeling is capable of predicting trend from noisy experimental data, such that simulation data better portrays the variation due to parameters.
Figure 5.15: Comparison of regression models based on ANN simulated and experimental data for models of increasing order (1) linear and interactions (2) full quadratic (3) squared and interactions (4) full cubic.

5.5.2.3 Regression modeling

The ANN simulated data was coded such that the parameter range falls between -1 and 1 prior to stepwise regression modeling. A linear model was considered adequate for recovery; the ANOVA results and model statistics are shown in Tables 5.12 and 5.13 respectively. The model successfully passed ANOVA significance and lack of fit test with a very low probability value ($P_{model > F} = 1.9 \times 10^{-9}$). The goodness of fit of the model was lower than the iron recovery model as expected, but good enough to be acceptable. An $R^2 = 0.78$ and $R^2_{adj} = 0.76$ show a moderate correlation without over fitting.

Table 5.12: ANOVA results for recovery model

<table>
<thead>
<tr>
<th>Sources of variation</th>
<th>Sum of squares</th>
<th>Degrees of freedom</th>
<th>Mean square</th>
<th>F value</th>
<th>Prob ($P &gt; F$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1777.2</td>
<td>2</td>
<td>888.62</td>
<td>46.26</td>
<td>$1.9 \times 10^{-9}$</td>
</tr>
<tr>
<td>Residual</td>
<td>518.62</td>
<td>27</td>
<td>19.21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOF Error</td>
<td>104.34</td>
<td>4</td>
<td>26.08</td>
<td>1.4481</td>
<td>0.250</td>
</tr>
<tr>
<td>Pure Error</td>
<td>414.28</td>
<td>23</td>
<td>18.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2295.8</td>
<td>29</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = 0.78$, $R = 0.88$, Adjusted $R^2 = 0.76$
Recovery = $b_0 + b_1x_1 + b_2x_2$

where: $x_1 =$ coded value of pinch valve open duration

$x_2 =$ coded value of pinch valve closed duration

$x_3 =$ coded value of bowl speed

The p-value < 0.001 for all coefficients showing very strong evidence against the null hypothesis in favour of the alternative, implying that the variation in recovery is more likely to be a result of the effect of changes in pinch valve timing (PVO and PVC), than it is to be a random change. VIF =1.005 for both coefficients, shows low co-linearity. Increasing PVO and reducing PVC increased the recovery; this is expected as mass yield increases. Although, bowl speed had no significant contribution to be admissible in the gold recovery model within the parameter range considered it is contrary to the expected separation mechanism. Increasing bowl speed is expected to increase mass yield and therefore recovery. This disparity is due to noisy experimental data. The recovery model may not adequately describe the effect of varying the three control variables, which may in turn affect optimization.

Stepwise regression modeling yielded a quadratic upgrade ratio model with significant PVO x BS and PVO x PVC interactions. All three variables had significant effect on the upgrade ratio. The model gave good prediction with an $R^2$ and $R^2_{adj}$ values of 0.88 and 0.86 respectively. Table 5.14 shows the upgrade model.
Table 5.14: Regression model for gold upgrade ratio

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>P value</th>
<th>Std Error</th>
<th>-95%</th>
<th>95%</th>
<th>t Stat</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_0$</td>
<td>1.7</td>
<td>&lt; 0.001</td>
<td>0.1</td>
<td>1.4</td>
<td>2.0</td>
<td>11.9</td>
</tr>
<tr>
<td>$b_1$</td>
<td>-1.1</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>-1.4</td>
<td>-0.7</td>
<td>-6.9</td>
</tr>
<tr>
<td>$b_2$</td>
<td>-1.0</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>-1.4</td>
<td>-0.6</td>
<td>-5.1</td>
</tr>
<tr>
<td>$b_3$</td>
<td>-1.0</td>
<td>&lt; 0.001</td>
<td>0.2</td>
<td>-1.4</td>
<td>-0.5</td>
<td>-4.5</td>
</tr>
<tr>
<td>$b_4$</td>
<td>0.6</td>
<td>&lt; 0.001</td>
<td>0.1</td>
<td>0.4</td>
<td>0.9</td>
<td>4.5</td>
</tr>
<tr>
<td>$b_5$</td>
<td>-0.4</td>
<td>0.003</td>
<td>0.1</td>
<td>-0.7</td>
<td>-0.2</td>
<td>-3.4</td>
</tr>
<tr>
<td>$b_6$</td>
<td>0.2</td>
<td>0.02</td>
<td>0.1</td>
<td>0.0</td>
<td>0.3</td>
<td>2.5</td>
</tr>
<tr>
<td>$b_7$</td>
<td>-0.4</td>
<td>0.08</td>
<td>0.2</td>
<td>-0.9</td>
<td>0.1</td>
<td>-1.8</td>
</tr>
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</table>

Upgrade ratio = $b_0 + b_1 x_1 + b_2 x_3^2 + b_3 x_1 x_3 + b_4 x_2^2 + b_5 x_1^2 + b_6 x_1 x_2 + b_7 x_3$  

where: $x_1$ = coded value of pinch valve open duration  
$x_2$ = coded value of pinch valve closed duration  
$x_3$ = coded value of bowl speed

The p-value is less than 0.01 for coefficients $b_0$ to $b_5$ showing very strong evidence against the null hypothesis in favour of the alternative whilst for $b_6$ and $b_7$ the evidence against the null hypothesis is moderate. The model shows that increasing PVO has the greatest impact on reducing upgrade ratio, followed by bowl speed and interaction effects between bowl speed and PVO. This is consistent with the expected CVD separation mechanism. Increasing the PVC and interaction between PVO and PVC increases upgrade ratio. Table 5.15 shows the ANOVA results for the model showing a low Probability ($P_{model} > F = 1.17 \times 10^{-8}$) showing the model passes the significance test.

Table 5.15: Analysis of variance (ANOVA) results for upgrade ratio model

<table>
<thead>
<tr>
<th>Sources of variation</th>
<th>Sum of squares</th>
<th>Degrees of freedom</th>
<th>Mean square</th>
<th>F-value</th>
<th>Prob (P) &gt;F</th>
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<tbody>
<tr>
<td>Regression</td>
<td>12.03</td>
<td>7</td>
<td>1.72</td>
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<tr>
<td>Residual</td>
<td>1.674</td>
<td>22</td>
<td>0.076</td>
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<tr>
<td>Total</td>
<td>13.71</td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

$R^2 = 0.88$, $R = 0.94$, Adjusted $R^2 = 0.84$

5.5.2.4 Formulation of optimization problem

The optimization problem is formulated as a minimization of a vector of objectives $\mathbf{F}(\mathbf{x})$ constituting a multi objective optimization problem that is subject to boundary constraints shown below.
Minimize \( \mathbf{F}(\mathbf{x}) = [-\mathbf{R}(x_1, x_2, x_3) - \mathbf{U}_r(x_1, x_2, x_3)] = [f(1), f(1)] \)
subject to:
\[-1 \leq x_1 \leq 1 \]
\[-1 \leq x_2 \leq 1 \]
\[-1 \leq x_3 \leq 1 \]
where \( x_1 \) is the coded pinch valve open duration, \( x_2 \) is the coded pinch valve closed duration, \( x_3 \) is the coded bowl speed, \( \mathbf{R} \) is gold recovery and \( \mathbf{U}_r \) is gold upgrade ratio.

\[
f(1) = -19.3 - 8.2x_1 + 4.2x_2 \tag{5.7}
\]
\[
f(2) = -1.7 + 1.1x_1 + x_3^2 + x_1x_3 - 0.6x_2^2 + 0.4x_1^2 - 0.2x_1x_2 + 0.4x_3 \tag{5.8}
\]
But since \( f(1) \) and \( f(2) \) are competing objectives, there is no unique solution to \( \mathbf{F}(\mathbf{x}) \). Instead, the concept of non-inferiority is used to characterize the objectives. A non-inferior solution is one in which an improvement in one objective requires a degradation of another which characteristic of the relationship between concentrate grade (and therefore upgrade ratio) and recovery for mineral processing operations. Since \( \mathbf{F}(\mathbf{x}) \) maps parameter space into objective function space, optimization involves identifying the non-inferior solution (also known as Pareto solution) in the objective space using genetic algorithm search techniques.

### 5.5.2.5 Optimization results

Figure 5.16 shows the Pareto optimum results for gold. The \textit{NNREGA} results envelop the initial experimental results, Figure 5.16 (a), coinciding with some of the extreme points whilst identifying other non-dominated combinations of upgrade ratio and recovery. Figure 5.16 (b) shows experimental validation results of the predicted optimum solution. There is a good correlation of the predicted results and experimentally validation results, which shows good prediction power of the \textit{NNREGA} approach, despite the noisy recovery results. The \textit{NNREGA} procedure is therefore capable of locating control parameters that can yield an improvement in CVD performance moving from the initial experimental results.
Figure 5.16: Pareto optimum solution for gold showing (a) that the predicted optimum results envelopes the statistical experimental results indicating an improvement in metallurgical performance (b) experimental validation of predicted optimum results indicating good prediction.

Table 5.16 gives the corresponding parameter levels for the Pareto optimum solution as determined by the NNREGA approach and the experimental validation results. Overall, the results demonstrate the usefulness of the NNREGA approach for simultaneous optimisation of grade and recovery for the CVD. Providing both the grade versus recovery operating line and the means to tune the machine in order to achieve optimum performance. The results also shows that greater than 20% of the gold lost to final tails at the Myra Falls plant is recoverable by the CVD yielding a concentrate with greater than twice the feed grade to the CVD.
Table 5.16: Pareto optimum and experimental validation results for gold

<table>
<thead>
<tr>
<th>Variable levels</th>
<th>Pareto Predicted</th>
<th>Experimental validation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recovery (%)</td>
<td>Upgrade ratio (%)</td>
</tr>
<tr>
<td>PVO (s)</td>
<td>PVC (s)</td>
<td>BS (g)</td>
</tr>
<tr>
<td>0.4</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>0.4</td>
<td>5</td>
<td>34</td>
</tr>
<tr>
<td>0.4</td>
<td>5</td>
<td>40</td>
</tr>
<tr>
<td>0.3</td>
<td>5</td>
<td>48</td>
</tr>
<tr>
<td>0.3</td>
<td>5</td>
<td>50</td>
</tr>
<tr>
<td>0.3</td>
<td>5</td>
<td>55</td>
</tr>
<tr>
<td>0.2</td>
<td>5</td>
<td>60</td>
</tr>
<tr>
<td>0.2</td>
<td>11</td>
<td>64</td>
</tr>
<tr>
<td>0.2</td>
<td>12</td>
<td>60</td>
</tr>
</tbody>
</table>

The results show that higher pinch valve open duration increases gold recovery whilst lowering the pinch valve open duration increases upgrade ratio at the expense of recovery. Increasing the bowl speed increased the upgrade ratio; this trend is not expected to continue beyond 70 g as evidenced by the bowl speed of 64 g and 69 g. The most important finding here is that using the NNREGA approach, the performance improvement path for the CVD can be predicted despite noisy experimental data. The procedure can also be used iteratively for continuous performance improvement. Figure 5.17 shows response surfaces, generated from experimental data. The response surfaces show non-linear variable interactions for both grade and recovery. An optimization approach for the CVD should be capable of handling the interactions between variables as characterized by the response surfaces.

Analysis of the response surfaces and the models generating them gives insight to the concentration mechanism of the CVD. Since bowl speed has a significant effect on recovery, which is a function of both upgrade ratio and mass yield, the increase in recovery with increasing bowl speed is due to increase in the rate of sedimentation as a result of the centrifugal force field coupled with increasing mass yield due to the increase in concentrate discharge. Further increasing the bowl speed beyond the optimum leads to particle bed compaction, which results in minimal particle transfer in the concentration ring. Increasing pinch valve closed duration increases particle residence time in the concentrate ring, promoting for particle separation as a result of migration, and percolation. Increasing pinch valve closed duration increases the extent to which lighter particles can be displaced by heavier ones. However, at too high bowl speed no upgrading will
occur in the concentration ring despite high pinch valve closed duration, due to bed compaction. Further increasing the PVC lowers the mass yield and therefore recovery.

Figure 5.17: Recovery and grade response surfaces for gold.

The recovery response surface shows that the optimum BS and PVC for recovery are in the middle of the feasible ranges. It is interesting to note that the regions containing the maximum recovery and grade as determined by response surfaces are similar to those predicted using NNREGA approach, however response surface methods cannot efficiently optimise both objectives as achieved through the NNREGA approach.
5.6 Full scale CVD42 optimization

This section presents full-scale CVD42 optimization results using iron as a proxy for gold bearing sulphides. For the full-scale CVD testing, there was not much flexibility for machine installation because of the machine size and safety requirements. This had potential to affect the uniformity of the feed presented to the CVD during testing. Due to pumping fluctuations and variations in the flotation plant, the level of pulp in the reservoir was observed to fluctuate which consequently resulted in variation in feed pulp density and flow rate to the CVD. These variations are more significant for full-scale tests due to the proportion of the feed stream processed by the machine. The pulp density and feed rate were therefore measured at the beginning and end of each test, to account for any variation during testing. When there was a small difference in the measured feed rates, an average of the two readings was used and when there was a large difference (above 0.5 tph) the results were rejected and the test was repeated. Figure 5.18 shows how the feed flow rate to the CVD42 was measured. The whole stream was diverted into a barrel and the time taken to fill up to the 160 L mark was recorded for the feed and concentrate streams.

Figure 5.18: Measuring flow rate using a barrel.

This method was found to be more reliable for measuring flow rate than the readings obtained from a flow meter installed on the feed stream. An obvious weakness of the reading was how to ensure that the pulp and not the froth as observed in Figure 5.18, was used for volume
measurement. Thus after every flow rate measurement time was allowed for the froth to subside and the pulp level confirmed the measurement was rejected if the pulp level was above or below the 160 L mark. In order to reduce measurement error introduced by variation in reaction time when timing the flow rate, the same operator measure flow time for all tests.

Initial scoping tests were conducted to determine the minimum and maximum parameter settings by varying the parameter levels and visually inspecting the product. The approach for defining the design space in Chapter four was applied. The minimum and maximum for pinch valve duration are limited by the mass yield requirements. For this application the maximum mass yield was set at 20%. Table 5.17 shows control parameter range determined for the CVD42 application.

Table 5.17: Control parameter range.

<table>
<thead>
<tr>
<th>Level</th>
<th>PVO (s)</th>
<th>PVC (s)</th>
<th>BS (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>0.35</td>
<td>4</td>
<td>26</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.8</td>
<td>15</td>
<td>86</td>
</tr>
</tbody>
</table>

In order to avoid plant upset, at the beginning of each testing period a standard start-up procedure developed with the Nyrstar metallurgical team was used. In order to allow for machine stabilisation, 30 minutes was allowed between adjusting parameters and initial sampling for each test. Sample cutters of the same width and volume were used to collect feed, tailings and concentrate samples by cutting across the whole stream every 15 minutes for an hour. The collected samples were mixed in a bucket and weighed prior to dewatering and drying. Riffled samples of tailings, concentrate and feed were assayed for gold silver and base metals on site at the Myra Falls assaying laboratory on site. Some duplicate samples were sent to IPL commercial laboratory and the results were agreeable. Assay results, flow rate measurements and density were used for metallurgical accounting. And the results are shown in the following section.

5.6.1 Full scale CVD42 optimization using iron as indicator for sulphides

This section presents the NNREGA optimization results for iron as an indicator of pyrite and therefore base metal sulphides recovery using a full scale CVD42. The objective was to demonstrate application of the optimization procedure in an actual operation subject to the daily plant variations.
5.6.1.1 Statistical experimental results

Table 5.18 shows experimental results for 23 statistically designed experiments for iron consisting of eight $2^3$ factorial experimental runs, three centre point repeats and circumscribed central composite designs.

Table 5.18: Statistical design experiments results for iron.

<table>
<thead>
<tr>
<th>PVO (s)</th>
<th>PVC (s)</th>
<th>BS (g)</th>
<th>Feed rate (tph)</th>
<th>Feed grade (%)</th>
<th>Tail grade (%)</th>
<th>Concentrate grade (%)</th>
<th>Mass yield (%)</th>
<th>Upgrade ratio (%)</th>
<th>Recovery (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.35</td>
<td>15</td>
<td>80</td>
<td>23</td>
<td>8.9</td>
<td>9.3</td>
<td>16.3</td>
<td>10.9</td>
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<td>20.0</td>
</tr>
<tr>
<td>0.40</td>
<td>15</td>
<td>60</td>
<td>20</td>
<td>9.6</td>
<td>9.6</td>
<td>13.6</td>
<td>7.7</td>
<td>1.4</td>
<td>10.9</td>
</tr>
<tr>
<td>0.40</td>
<td>6</td>
<td>30</td>
<td>20</td>
<td>9.6</td>
<td>9.7</td>
<td>15.4</td>
<td>3.7</td>
<td>1.6</td>
<td>6.0</td>
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<tr>
<td>0.40</td>
<td>15</td>
<td>30</td>
<td>21</td>
<td>10.4</td>
<td>11.0</td>
<td>17.4</td>
<td>2.3</td>
<td>1.7</td>
<td>3.9</td>
</tr>
<tr>
<td>0.40</td>
<td>10</td>
<td>60</td>
<td>21</td>
<td>11.4</td>
<td>11.3</td>
<td>16.1</td>
<td>8.9</td>
<td>1.4</td>
<td>12.6</td>
</tr>
<tr>
<td>0.75</td>
<td>10</td>
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<td>22</td>
<td>11.6</td>
<td>10.0</td>
<td>14.2</td>
<td>21.5</td>
<td>1.2</td>
<td>26.2</td>
</tr>
<tr>
<td>0.60</td>
<td>15</td>
<td>30</td>
<td>21</td>
<td>11.7</td>
<td>11.3</td>
<td>14.4</td>
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<td>11.6</td>
</tr>
<tr>
<td>0.40</td>
<td>4</td>
<td>60</td>
<td>22</td>
<td>11.2</td>
<td>10.1</td>
<td>14.5</td>
<td>13.4</td>
<td>1.3</td>
<td>17.4</td>
</tr>
<tr>
<td>0.60</td>
<td>4</td>
<td>30</td>
<td>21</td>
<td>11.0</td>
<td>10.5</td>
<td>11.7</td>
<td>10.0</td>
<td>1.1</td>
<td>10.7</td>
</tr>
<tr>
<td>0.40</td>
<td>10</td>
<td>60</td>
<td>20</td>
<td>11.1</td>
<td>10.6</td>
<td>15.0</td>
<td>7.5</td>
<td>1.4</td>
<td>10.2</td>
</tr>
<tr>
<td>0.40</td>
<td>20</td>
<td>60</td>
<td>21</td>
<td>11.9</td>
<td>11.5</td>
<td>15.6</td>
<td>6.5</td>
<td>1.3</td>
<td>8.5</td>
</tr>
<tr>
<td>0.35</td>
<td>10</td>
<td>60</td>
<td>22</td>
<td>12.0</td>
<td>11.6</td>
<td>16.9</td>
<td>6.2</td>
<td>1.4</td>
<td>8.7</td>
</tr>
<tr>
<td>0.35</td>
<td>6</td>
<td>76</td>
<td>20</td>
<td>12.0</td>
<td>10.1</td>
<td>20.0</td>
<td>9.1</td>
<td>1.7</td>
<td>15.1</td>
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<td>0.60</td>
<td>6</td>
<td>70</td>
<td>21</td>
<td>12.0</td>
<td>10.3</td>
<td>16.1</td>
<td>23.6</td>
<td>1.3</td>
<td>31.7</td>
</tr>
<tr>
<td>0.40</td>
<td>15</td>
<td>30</td>
<td>21</td>
<td>11.0</td>
<td>10.7</td>
<td>18.0</td>
<td>2.9</td>
<td>1.6</td>
<td>4.7</td>
</tr>
<tr>
<td>0.60</td>
<td>15</td>
<td>80</td>
<td>22</td>
<td>11.3</td>
<td>9.5</td>
<td>18.0</td>
<td>18.6</td>
<td>1.6</td>
<td>29.5</td>
</tr>
<tr>
<td>0.40</td>
<td>10</td>
<td>26</td>
<td>19</td>
<td>12.7</td>
<td>11.7</td>
<td>13.3</td>
<td>3.7</td>
<td>1.1</td>
<td>3.9</td>
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<tr>
<td>0.80</td>
<td>30</td>
<td>30</td>
<td>20</td>
<td>13.5</td>
<td>13.0</td>
<td>16.6</td>
<td>5.0</td>
<td>1.2</td>
<td>6.1</td>
</tr>
<tr>
<td>0.40</td>
<td>10</td>
<td>86</td>
<td>22</td>
<td>12.4</td>
<td>10.1</td>
<td>18.5</td>
<td>21.1</td>
<td>1.5</td>
<td>31.5</td>
</tr>
<tr>
<td>0.40</td>
<td>15</td>
<td>60</td>
<td>21</td>
<td>12.2</td>
<td>11.2</td>
<td>20.2</td>
<td>9.2</td>
<td>1.7</td>
<td>15.2</td>
</tr>
<tr>
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<td>8.2</td>
<td>6.8</td>
<td>21.0</td>
<td>2.1</td>
<td>2.6</td>
<td>5.3</td>
</tr>
<tr>
<td>0.35</td>
<td>15</td>
<td>60</td>
<td>20</td>
<td>10.1</td>
<td>10.2</td>
<td>20.4</td>
<td>7.4</td>
<td>2.0</td>
<td>14.9</td>
</tr>
<tr>
<td>0.35</td>
<td>15</td>
<td>80</td>
<td>20</td>
<td>10.7</td>
<td>9.3</td>
<td>22.4</td>
<td>12.6</td>
<td>2.1</td>
<td>26.3</td>
</tr>
</tbody>
</table>
Iron recovery ranged from 3.9 to 31.5 % whilst upgrade ratio ranged from 1.1 to 2.6. Low pinch valve open duration and high pinch valve closed duration and increased iron upgrading, whilst high pinch valve open duration and bowl speed and low pinch valve closed duration increased recovery. To reduce the impact of fluctuating feed grade on optimization, upgrade ratio was used instead of concentrate grade.

5.6.1.2 Artificial neural network training results

The 23 experimental data sets were used as input for training a feed forward back propagation neural network. The same procedure used for the pilot scale ANN training was followed in training the recovery and upgrade ratio neural networks for the full scale CVD42. Figure 5.19 shows screenshots for ANN training showing variation of training, validation and testing errors for a recovery (a) and upgrade ratio (b) networks. The recovery network started over fitting after the 9th epoch, when the validation error started to increase whilst the training error continued to decrease. Network training stopped when the validation error increased for six epochs, which occurred at iteration 15. The best performance was therefore MSE = 0.029 at epoch 9 as indicated by the intersection of the dotted lines.

Figure 5.19: Parity plots between epoch and mean square error for training of a recovery network (a) and upgrade ratio network (b). Showing the training error in (blue), validation error in (green), and testing error in (red).

The best network was selected by varying the number of hidden neurons and monitoring network performance. For recovery, the best network obtained was a [3 4 1] network. A [3 9 1]
network yielded the best training results for upgrade ratio. Training stopped when the validation error remained constant for four epochs that occurred at iteration 10 as shown in Figure 5.19 (b), the best validation error of 0.12 occurred at iteration 6.

Figure 5.20 shows comparison of experimental and ANN prediction data. The correlation coefficients between measured and predicted recovery and upgrade ratio are 0.93 and 0.78 respectively.

![Figure 5.20: Scatter plot for ANN models (a) recovery and (b) upgrade ratio.](image)

### 5.6.1.3 Regression modeling

The trained neural networks were used to generate data for regression by simulating the parameter combinations used in the experimental tests. Stepwise regression modeling for recovery yielded a quadratic model with significant variable interactions. Table 5.19 shows the recovery model with statistics for model coefficients. The significance of each coefficient was determined using the t-test and p-values. Most of the coefficients had p-value < 0.001 showing very strong evidence against the null hypothesis in favour of the alternative. Thus the coefficients are significant. For the selected model, VIF < 10 for all coefficients showing low multicollinearity among regressors.
Table 5.19: Recovery model coefficients

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>P value</th>
<th>Std Error</th>
<th>-95%</th>
<th>95%</th>
<th>t Stat</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_0$</td>
<td>18.19</td>
<td>&lt; 0.001</td>
<td>0.9</td>
<td>16.37</td>
<td>20.01</td>
<td>21.10</td>
</tr>
<tr>
<td>$b_1$</td>
<td>11.24</td>
<td>&lt; 0.001</td>
<td>0.7</td>
<td>9.86</td>
<td>12.63</td>
<td>17.15</td>
</tr>
<tr>
<td>$b_2$</td>
<td>-3.582</td>
<td>0.02</td>
<td>1.4</td>
<td>-6.51</td>
<td>-0.65</td>
<td>-2.58</td>
</tr>
<tr>
<td>$b_3$</td>
<td>6.317</td>
<td>&lt; 0.001</td>
<td>0.7</td>
<td>4.79</td>
<td>7.84</td>
<td>8.73</td>
</tr>
<tr>
<td>$b_4$</td>
<td>-3.542</td>
<td>&lt; 0.001</td>
<td>0.9</td>
<td>-5.39</td>
<td>-1.7</td>
<td>-4.05</td>
</tr>
<tr>
<td>$b_5$</td>
<td>2.632</td>
<td>&lt; 0.01</td>
<td>0.9</td>
<td>0.66</td>
<td>4.61</td>
<td>2.81</td>
</tr>
</tbody>
</table>

Recovery = $b_0 + b_1 x_1^2 + b_2 x_2^2 + b_3 x_3 + b_4 x_2 x_3 + b_5 x_1 x_3$

where: 
$x_1$ = coded value of pinch valve open duration
$x_2$ = coded value of pinch valve closed duration
$x_3$ = coded value of bowl speed

Bowl speed and pinch valve open duration had the most significant effect on iron recovery and (BS x PVO, PVO x PVC) interaction effects were significant. Increasing PVO and BS increased iron recovery.

Results of Analysis of variance (ANOVA) for the recovery model are given in Table 5.20. A second order model with third order interactions had the best fit for recovery. The F-test with a very low probability value ($P_{model} > F = 9.93 \times 10^{-13}$) shows that the model is significant. The values of the coefficient of determination ($R^2 = 0.973$) and the adjusted coefficient of determination $R^2_{adj} = 0.965$, shows that only 2.7 % of the total variation is not explained by the model. The small difference between $R^2_{adj}$ and $R^2$ shows that the high coefficients of determination is not due to addition of insignificant coefficients but rather a good fitting model with excellent correlation between the independent variables.

Table 5.20: Analysis of variance (ANOVA) results for recovery model

<table>
<thead>
<tr>
<th>Sources of Variation</th>
<th>Sum of squares</th>
<th>Degrees of freedom</th>
<th>Mean square</th>
<th>$F$ value</th>
<th>Prob (P) &gt; $F$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1408.7</td>
<td>5</td>
<td>281.74</td>
<td>122.99</td>
<td>$9.93 \times 10^{-13}$</td>
</tr>
<tr>
<td>Residual</td>
<td>38.94</td>
<td>17</td>
<td>2.291</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1447.7</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = 0.97$, $R = 0.98$, Adjusted $R^2 = 0.97$

Table 5.21 gives the ANOVA results for the upgrade ratio model. The model passed the significance and lack of fit test with a $R^2 = 0.59$ and $R^2_{adj} = 0.55$ showing moderate correlation
without over-fitting and a low probability value ($P_{\text{model}} > F = 1.28 \times 10^{-4}$) showing the model is significant. Low iron upgrade ratios makes determination of the effect of change in variable levels more difficult resulting in a model with a low correlation coefficient. Table 5.22 shows the upgrade ratio model with the P-value and t-statistics for each coefficient.

Table 5.21: Analysis of variance (ANOVA) results for upgrade ratio model

<table>
<thead>
<tr>
<th>Sources of variation</th>
<th>Sum of squares</th>
<th>Degrees of freedom</th>
<th>Mean square</th>
<th>F- value</th>
<th>Prob (P) &gt;F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1.565</td>
<td>2</td>
<td>0.783</td>
<td>14.51</td>
<td>1.28 x 10^{-4}</td>
</tr>
<tr>
<td>Residual</td>
<td>1.078</td>
<td>20</td>
<td>0.054</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2.643</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = 0.59$, $R = 0.78$, Adjusted $R^2 = 0.55$

Table 5.22: Upgrade ratio model coefficients

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>P value</th>
<th>Std Error</th>
<th>-95%</th>
<th>95%</th>
<th>t-Stat</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_0$</td>
<td>1.52</td>
<td>&lt; 0.001</td>
<td>0.06</td>
<td>1.4</td>
<td>1.6</td>
<td>26.34</td>
</tr>
<tr>
<td>$b_1$</td>
<td>-0.73</td>
<td>&lt; 0.001</td>
<td>0.14</td>
<td>-1.02</td>
<td>-0.45</td>
<td>-5.387</td>
</tr>
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Upgrade ratio = $b_0 + b_1 x_1 x_2^2 + b_2 x_2 x_3^2$

where:

$x_1$ = coded value of pinch valve open duration

$x_2$ = coded value of pinch valve closed duration

$x_3$ = coded value of bowl speed

The p-value is low for all coefficients showing strong evidence against the null hypothesis in favour of the alternative. VIF is less than 10 for all coefficients showing low co-linearity between the control parameters. Interaction between bowl speed and PVO reduces upgrade ratio whilst increasing BS and PVC interactions increases upgrade ratio. This is expected, as increasing pinch valve open duration reduces the time allowed for upgrading in the concentrate ring. When coupled with an increase in the bowl speed, it results in more particles exiting the pinch valves without further upgrading. If there is no bed compaction, increasing both bowl speed and together with pinch valve closed duration increases the upgrade ratio.
5.6.1.4 **Formulation of Optimization problem**

The optimization problem was formulated as a minimization of a vector of objectives $F(x)$, subject to boundary constraints shown below:

Minimize $F(x) = [-R(x_1, x_2, x_3) - Ur(x_1, x_2, x_3) = [f(1), f(1)]$

Subject to:
- $-1 \leq x_1 \leq 1$
- $-1 \leq x_2 \leq 1$
- $-1 \leq x_3 \leq 1$

where $x_1$ is the coded pinch valve open duration, $x_2$ is the coded pinch valve closed duration, $x_3$ is the coded bowl speed, $R$ is gold recovery and $Ur$ is gold upgrade ratio.

$$f(1) = -18.19 - 11.24x_3 + 3.582x_1^2 - 6.317x_1 + 3.542x_2 - 2.632x_1x_3$$  \hspace{1cm}  \text{(5.11)}$$

$$f(2) = -1.523 + 0.733x_1x_3 - 0.645x_2x_3^2$$  \hspace{1cm}  \text{(5.12)}$$

5.6.1.5 **Optimization results**

Figure 5.12 shows the Pareto optimum solutions obtained using the NNREGA approach and Table 5.23 shows the corresponding variable levels for the predicted optimum solutions. Experimental validation of the optimum results show good predicted for iron. There is reasonable correlation of the predicted results and experimental validation results in (a). The results show that increasing pinch valve open duration and reducing pinch valve closed duration increases recovery, whilst lowering the pinch valve open duration and increasing pinch valve closed duration increases upgrade ratio at the expense of recovery.
Figure 5.21: Pareto optimum solution in response function space showing (a) the predicted optimum results and experimental validation results, (b) showing that the predicted optimum results forms an envelope above the statistical experimental results, thus predicting improved metallurgical performance.

Table 5.23: Pareto optimum results and validation.

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<tr>
<th>Variable levels</th>
<th>Pareto Predicted</th>
<th>Experimental validation</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Recovery (%)</td>
<td>Upgrade ratio (%)</td>
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<td>PVC (s)</td>
<td>BS (g)</td>
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Unlike the pilot scale results, high bowl speed produced the best metallurgical performance for the CVD42. This maybe attributed to changes in ore characteristics; more fines would require a higher centrifugal force for efficient separation. Alternatively it can be attributed to the upgrade ratio model, which may have failed to fully account for the effect of variables due to a low correlation coefficient. Both full scale CVD42 and pilot scale CVD6 results show that that the NNREGA predicted optimum results envelop the initial statistical experimental results, coinciding with some of the extreme points whilst identifying other non dominated combinations of upgrade ratio and recovery. Within a 95% confidence interval, the predicted Pareto optimum results are significantly superior to the initial experimental results.
Figure 5.22 shows comparison of the operating lines for the CVD 6 and 42 showing that the full scale machine outperformed the pilot scale machine at high mass yield. At lower mass yield there is no significant difference in the performance of the machines. Such a comparison based on optimum operating lines for the different machines treating the same ore is a useful basis for scale up and can also inform design improvements.

![Comparison of operating lines for the CVD 6 and 42.](image)

**5.7 Particle separation in a CVD**

The parametric equations provide insight on the CVD particle separation mechanism. Results for iron and gold show the significant effect of bowl speed, pinch valve open duration and pinch valve closed duration on both upgrade ratio and recovery. These results demonstrate that particle separation in the concentrate ring has a significant contribution to CVD metallurgical performance. Increasing bowl speed increases recovery and reduces concentrate upgrade ratio.

Particle separation along the short cone is mainly due to differential settling. As particles are introduced to the rotating bowl they are deflected to the bowl wall, the change in velocity is a function of centrifugal acceleration, particle size, density and shape, and fluid density and viscosity. Particles are stratified into different transport modes based on their properties. All particles in the rolling transport mode (coarse dense) and part of the particles in the saltation mode report to the CVD concentrate ring. Particles in the suspensive mode overflow the bowl and report to tailings. The superficial velocity ring, positioned above the concentrate ring, splits the stratified
particle bed. Increasing bowl speed increases the intensity of the centrifugal force field thus increases stratification along the CVD short bowl whilst lowering the particle residence time.

A stratified particle bed enters the concentrate ring, which is initially fluidized where further upgrading occurs. Particle separation in the concentrate ring can be inferred from the effect of pinch valve duration on upgrade ratio. The empirical models for both gold and iron show upgrade ratio increases with increasing pinch valve closed duration and decreasing pinch valve open duration. Upgrade ratio decreases with interactions between increasing bowl speed and pinch valve open duration, and increases with interaction between increasing bowl speed and pinch valve closed duration. Increasing both pinch valve closed and pinch valve open duration decreased upgrade ratio. Particle separation in the concentrate ring is a result of percolation and migration and the Ungarish (1993) three layer model can be used to describe particle movement in the fluidized concentrate ring. Fluidization serves to dilate the bed, preventing compaction and enabling mass transfer between material subsequently entering the ring and that already in the ring. Separation is both by density and size and depends on the voidage, which is a function of both fluidization flow rate and bowl speed. Increasing bowl speed increases particle movement, but too high bowl speed leads to bed compaction hindering further upgrading. Particle segregation as a result of sizing increases with voidage, whilst particle segregation due to sorting decreases with increasing voidage. Increasing pinch valve closed duration therefore allows more time for particle migration, leading to a higher upgrade ratio. The pinch valve open duration should be high enough to allow only upgraded material out of the concentrate ring.

Considering the two concentration zones in a CVD, increasing bowl speed would increase stratification in the short bowl while causing bed compaction within the concentrate ring and inhibiting further upgrading. A threshold bowl speed thus exists, which maximizes stratification without compacting the bed. Increasing the bowl speed increases the effective centrifugal force causing a reduction in separation density and an increase in the difference in settling velocities of particles. Reduction in separation density results in dilution of the high specific density product by lower density particles.

5.8 Summary

The \textit{NNREGA} approach was capable of predicting a combination of parameter settings that yielded improved metallurgical performance. Experimental validation of \textit{NNREGA} predicted results confirmed the usefulness of the procedure for tuning CVD control variables in order to
maximize metallurgical performance. *NNREGA* is capable of predicting optimum metallurgical performance regardless of noisy experimental data as shown by gold and iron results, and it produced satisfactory results for both pilot and full scale CVD optimization. For less noisy iron experimental data, less experimental runs can be used to train the neural network. When the experimental data is noisy, low order regression models are preferred as they can capture the trend without over fitting.

The strategic experimental design and ANN simulation used in the *NNREGA* approach reduces the number of experimental tests required for locating the process optima, cutting down on both the time and capital requirements. The approach allows for simultaneous optimization of grade and recovery, and the optimization solution is not a single optimum point, but rather a set of control parameter levels yielding non-dominated combinations of recovery and grade or upgrade ratio. This exploitation of the grade versus recovery relationship in mineral processing is novel, and allows for plant optimization separate from metal economics. The potential to integrate *NNREGA* as an optimization module in the CVD programmable logic control (PLC) is an essential step towards effective plant control.

The results obtained in this research confirms the uniqueness of CVD machines, as the operating range for pinch valve timing is 10 times higher than that used by Klein et al (2010). The results in this thesis show a clear recovery peak as a function of pinch valve timing, indicating quadratic effects, which is not so clear in Klein et al (2010). The optimum PVC for the machine used in this research was in the range of 10 - 15s. Increasing PVO is shown to reduce upgrade ratio, due to increase in the proportion of particles that bypass upgrading and report to CVD concentrates. Enough pinch valve open duration should be allowed to discharge only the upgraded layer of particles. When PVO is increased beyond a critical level, dilution of concentrates by gangue reduces upgrade ratio rendering recovery constant. The results therefore show the effect of machine variables and their interactions on CVD performance.
Chapter 6: Claims for original contributions and recommendations for future work

6.1 Conclusions and claims for original contributions

Mineral processing optimization has been centered on maximizing either grade or recovery. The few approaches used for simultaneous optimization of both grade and recovery required prior weighting of the objectives, and thus, were deterministic and yielded only one grade versus recovery solution. This classical approach to optimization involves combining the objectives into a single criterion to be optimized according to some utility function. In mineral processing, the utility function changes with mineral economics and varies from operation to operation. Given the competing relationship between grade and recovery, a single objective function with several constraints and a utility function is subject to metal economics and thus difficult to formulate for plant operators. Multi objective genetic algorithm optimization allows for the grade versus recovery operating line to be determined independent of metal economics. Then, based on metal economics, the optimum combination of concentrate grade (quality measurement) and recovery (quantity measurement) can be determined. Knowledge of the opposing nature of the grade versus recovery relationship has not yet been fully exploited in mineral processing optimization. This research is the first step in mineral processing optimization that sought to determine the operating line (combination of superior grade and recovery) independent of metal economics.

A novel hybrid optimization approach for tuning CVD operating conditions to obtain the optimum grade versus recovery operating line, which integrates artificial neural network, regression modeling and genetic algorithm was developed. The procedure was tested for optimization of pilot and full-scale CVD concentrators at Myra Falls. Part of the novelty of the NNREGA optimization approach is a reduction in the number of experimental tests required to explore a design region by using circumscribed central composite experimental design. Traditionally, either neural networks or regression modeling has been employed but not both. This research demonstrates that a hybrid ANN-Regression model can produce better parametric models for purposes of process optimization by exploiting the robustness of ANN to determine trends from noisy experimental data. Simulation using the ANN models generates less noisy data, which can be used to obtain better regression models. The NNREGA approach provides a tool for plant
operators to tune CVD machine variables in order to maximize metallurgical performance for any application. The procedure is applicable to other continuous centrifugal concentrators and can be used for any application which is likely to generate noisy experimental data, and has multiple interacting independent variables and more than one objective function with multiple constraints.

Mineral processing simulators, present on the market, use phenomenological models for unit processes to simulate processing circuits. Such models do not exist yet for continuous centrifugal concentration, and therefore no modules for these technologies exist in the mineral processing simulators. The NNREGA approach allows for continuous improvement and can be used as part of an operating strategy with potential for incorporation into the machine programmable logic control system as an optimization module. In addition it can be developed into a centrifugal concentrator module that can be integrated in the existing mineral processing simulators to enhance plant optimization.

Based on the results of the NNREGA approach, a basis for comparing performance and therefore scaling up for CVD machines was developed.

A novel bench scale test to assess ore amenability to CVD concentration was developed and tested. The test procedure allows application of CVD technology to be assessed using small sized samples, and also allows for benchmarking of operating CVDs. The results demonstrate that the Gravity Release Analysis procedure, is capable of predicting CVD application as it forms an envelop above the CVD results. Using this laboratory procedure, the maximum gravity recoverable gold bearing sulphides and the respective mass yield and grade of the concentrate can be predicted using small size samples. This has potential to increase application of the continuous centrifugal concentration technologies as it provides a mechanism of evaluating possible usage in new flowsheet designs.

Based on the Gravity Release Analysis procedure a quantitative measure of gravity amenability and gravity concentration kinetics, the gravity release index (GRI), was introduced. It can be used to identify the mineral species recoverable by gravity and quantify their amenability to gravity recovery. In addition, the relative abundance of the species, which is a useful guide in deciding whether to use batch or continuous centrifugal concentration, can be determined. Using the GRI, the presence of at least two gold bearing species and their relative abundances was determined for flotation tailings at Myra Falls. The results were confirmed by mineralogical analysis using a scanning electron microscope.
The use of gravity recovery indicator elements as the basis of gravity recovery of gold associated sulphides was introduced. Such as, when iron is mainly contained in sulphides and there are significant quantities of iron sulphides in the ore, then iron assays can be used as the basis of measuring sulphides recovery. When gold is associated with sulphides, then iron can be used as an indicator for gold recovery. The use of indicator elements can significantly reduce optimization costs since base metals can easily and quickly be assayed using the XRF.

Application of CVD technology for scavenging gold bearing sulphides from flotation tailings was demonstrated. The results of the tests show potential to scavenge gold bearing sulphides from flotation tailings for a massive sulphide deposit. The CVD recovered up to 32 % of the gold in flotation tails, accounting to 17.5 % of the total gold recovery. Although liberated gold is also recovered by the CVD, bulk of the gold recovered from flotation tails is in coarse middlings above 38 µm. The low-grade CVD concentrate can either be added to the base metal concentrates to increase gold credits or further ground to liberate the gold.

This research also clarified CVD concentration mechanism by demonstrating the effect of operating variables to machine performance. In particular, that increasing centrifugal force lowers the separation density, such that at high bowl speed the CVD concentrates tends to be diluted by low density minerals.

6.2 Recommendations for future work

The following aspects arising out of this research deserve to be followed up in future research work:

1. The operating lines predicted using the NNREGA approach enable comparison of units of different sizes. Differences in Pareto curves for different machines treating the same ore may inform design considerations.

2. Three variables (PVO, PVC and BS) were assessed in the current study; further tests can include ore specific variables. These are difficult to control especially for real ores, therefore synthetic ores with varying concentration criteria can be used to simulate ore of varying degrees of liberation.

3. Since the CVD is used for scavenging applications, it was assumed the feed would not require further grinding prior to concentration, therefore the Gravity release procedure was tested at the feed particle size only in this thesis. To obtain liberation related gravity
release, sequential comminution and Gravity release steps can be tested and the results compared to the standard GRG test.

4. Empirical models were used for this study, to enhance process understanding; phenomenological models of the CVD have to be developed.

5. Feed rate was not included as a variable in the current study, and was thus kept constant. To scale up CVD, further work which include feed rate, as a variable should be included.

6. The effect of fluidization on CVD performance was determine in previous studies (McLeavy, 2005), but, the contribution of fluidization to the mechanism of CVD concentration still need to be studied, especially how fluidization and rotational speed interact to effect particle separation. The contribution of bowl design to this interaction has to be assessed in order to ascertain if fluidization is of any significance to particle separation apart from particle transport out of the bowl.

7. Further GRA, pilot and full-scale CVD tests should be conducted in order to calibrate the gravity release index for use in flowsheet design.

8. The potential to integrate NNREGA as an optimization module in the CVD programmable logic control (PLC) has to be assessed.
Bibliography


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Appendices

Appendix A

CVD6 unit (A) synthetic ore test for 5% magnetite ore

<table>
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<th>PVO (s)</th>
<th>PVC (s)</th>
<th>Bs (G)</th>
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<th>Recovery (%)</th>
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Appendix B

CVD6 unit (A) synthetic ore test for 2% magnetite ore

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Appendix C

The table shows results for Model 1 assuming a bimodal system containing mainly GRG. First order kinetics is assumed to compute both the concentrate grade and recovery. The relative composition of the GRG and a recovery rate of 10 times higher than the gangue is assumed.

\[
G_{s-p} = \frac{A_f [1 - \exp(-s_y t)]}{A_f [1 - \exp(-s_y t)] + [1 - \exp (-s_h t)]}
\]

\[
R_{s-p} = \frac{w_{s-p}}{w_{s-f}} \times 100% = [1 - \exp(-s_y t)] \times 100%
\]

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Appendix D

The table shows results for Model 2 assuming two gold bearing mineral species. Mineral (A) representing GRG with a very high gravity recovery rate and high gold content compared to (B) GRGS than B. Where $A_f$ is the fractional weight of species A.

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\[
G_{Au-P} = \frac{G_{Au-A} \times A_f [1 - \exp (-s_A t)] + G_{Au-B} [1 - \exp (-s_B t)]}{A_f [1 - \exp (-s_A t)] + [1 - \exp (-s_B t)]}
\]

\[
R_{Au-P} = \frac{G_{Au-A} \times A_f [1 - \exp (-s_A t)] + G_{Au-B} [1 - \exp (-s_B t)]}{G_{Au-A} \times A_f + G_{Au-B}}
\]

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### Appendix E

#### Model 3 simulation data

| Time (s) | $P_{-W_B}$ | $P_{-W_C}$ | $P_{-W_D}$ | $P_{-R_B}$ | $P_{-R_C}$ | $P_{-R_D}$ | Recovery % | Grade (g/l) | Time (s) | $P_{-W_B}$ | $P_{-W_C}$ | $P_{-W_D}$ | $P_{-R_B}$ | $P_{-R_C}$ | $P_{-R_D}$ | Recovery % | Grade (g/l) |
|----------|-------------|-------------|-------------|------------|------------|------------|------------|-------------|----------|-------------|-------------|-------------|------------|------------|------------|------------|-------------|----------|
| 0.0      | 0.0         | 0.0         | 0.0         | 0.00       | 0.01       | 10         | 10         | 2           | 0.0      | 0.0         | 0.0         | 0.0         | 0.00       | 0.01       | 10         | 10         | 2           | 0.0      |
| 10       | 3           | 5           | 20          | 20         | 10         | 1           | 0.1        | 0.1         | 0.1       | 0.1         | 0.1         | 0.1         | 0.1        | 0.1        | 0.1        | 0.1        | 0.1         | 0.1       |
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# Appendix F1

## Myra Falls Final tails CVD6 test conditions

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## Appendix F2

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