An optimisation approach to investigate quality control of a product coal stockpile

By

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DECLARATION

I, the undersigned, hereby declare that the work contained in this dissertation, is my own original work and that I have not previously, in its entirety or in part, submitted it at any university for a degree.

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SUMMARY

Keywords: Coal beneficiation, dense medium separation, data mining, neural network, genetic algorithm

For any coal beneficiation group to reach the full financial potential in coal production, optimal coal cleaning processes are of great importance. The heterogenic nature of coal is the main constraint in producing a constant and accurate coal quality, meeting the client's requirements. Aside from the heterogenic nature of coal, inefficient quality control on coal product lines also contributes to a decrease in potential profit. Eliminating causes for inefficient quality control on a semi-soft coking coal production line is the focus of the investigation.

The current quality control strategy applied to a coking coal production line under investigation includes an operator using a trial and error method to manage the average ash quality on the coking coal stockpile. In order to reach a predefined ash accumulation set point, the operator is responsible for the manual adjustment of separation densities in five dense medium cyclones. The set point along with several other stockpile properties are calculated using a stockpile building management system, integrating all the appropriate on-line and off-line data from different data repositories. This control strategy among other process inconsistencies contributes to a sub-optimal quality control.

The main objective of the project is to investigate the benefits in replacing the manual quality control strategy with an optimised decision support solution able accommodate the operator with optimised SBS outputs to control the coking coal quality more efficiently and with higher throughput.

The performance of the optimised solution created, is compared to the performance of the current quality control system. The optimisation solution has the ability to control the ash accumulation around a set point with a smaller variance compared to the current control system. However, the lower throughput in some instances highlights inaccuracies within the optimisation solution. Measurements that are more representative will increase the performance of the optimisation solution.

OPSOMMING

Sleutelwoorde: Steenkool veredeling, digte medium skeiding, data ekstraksie, neural netwerk, genetiese algoritme

Om die volle finansiële potensiaal te verwerklik is optimale steenkool veredelings prosesse van uiters belang vir enige steenkool veredelings maatskappy. Die hoof beperking in die produsering van steenkool met konstante en akkurate kwaliteite, is die heterogeniese aard van steenkool. Buiten hierdie heterogeniese eienskap van steenkool, dra oneffektiewe prosesbeheer op steenkool kwaliteit ook by tot 'n afname in potensiële finanasiële opbrengste. Die oorhoofse fokus van die ondersoek, is die uitskakeling van oorsake vir swak kwaliteit beheer op'n kooks steenkool produksie lyn.

'n Operateur wat 'n probeer-en-tref metode volg in die beheer van die gemiddelde as kwaliteit op die steenkool bed, maak deel uit van die huidige beheerstrategie wat gebruikword op 'n kooks steenkool produksie lyn. Die operateur is verantwoordelik vir die verstelling met die hand op vyf digte-medium-skeiding siklone se skeidings digthede. Die verstellings word aangebring om 'n gedefineerde stelpunt te bereik. Die stelpunt asook sekere ander steenkool bed eienskappe word in 'n bed-bou-program bereken. Geskikte aanlyn en historiese data uit verskillende data banke word geïntegreer met die program vir toepaslike berekeninge. Die huidige beheerstrategie asook vele ander afwykings dra by tot die oneffektiewe kwaliteit beheer.

Die hoof doel van die projek is om die vervanging van die huidige beheerstrategie met 'n meer optimale strategie te ondersoek, vir resultate wat meer effektiewe kwaliteit beheer en hoër opbrengste genereer.

Die prestasies van die optimaliserings oplossing word met die prestasies van die huidige beheersisteem vergelyk. In vergelyking met die huidige beheersisteem, beheer die optimaliserings oplossing die as akkumulasie om 'n stelpunt met minder variasies. Nietemin, onderstreep laer opbrengste in sommige gevalle afwykings in die optimaliserings oplossing. Meer verteenwoordigende meetings sal die verrigting van die optimaliserings oplossing verbeter.

ACKNOWLEDGEMENTS

I would like to take this opportunity to acknowledge certain individuals contributing directly and/or indirectly to the completion of this dissertation. With their support, this dissertation is a product of true motivation, inspiration and guidance.

First, I must give thanks to my Maker and Lord. Rom 11:36: "For of Him, and through Him, and to Him, are all things: to whom be glory forever. Amen."

Then, I would like to thank my wife, for the patience, understanding and motivation in demanding times, as well as in the more successful times. Thank you for the selfless love and support.

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Jonathan Meyer from Exxaro helped me in the extraction of the appropriate data records from the coal beneficiation site. You went out of your way in providing me with the information, and I thank you for that.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AMSA	ArcelorMittal South Africa
CFD	Computational Fluid Dynamics
csv	comma-separated values
DMC	Dense Medium Cyclone
DMS	Dense Medium Separation
EPM	Écart probable moyen
GA	Genetic Algorithm
GG1 – GG6	Coal beneficiation plants 1 to 6
GHG	Greenhouse Gases
InSQL	Industrial Structured Query Language
KD	Knowledge Discovery
KPI	Key Performance Indicator
LIMS	Laboratory Information Management System
Mt	Mega tonnes
Mtpa	Mega tonnes per annum
NN	Neural Network
PCA	Principal Component Analysis
RD	Relative Density
ROM	Run-of-mine
SBS	Stockpile Building System
SQL	Structured Query Language
SSA	Sub-Saharan Africa

NOMENCLATURE

Variable	Description
E_p	Écart probable moyen (EPM) - describes the extent of possible misplaced particles in DMC operation.
D_{25}, D_{50}, D_{75}	Relative density cutpoint; particles have 25%, 50%, 75% chance at reporting to either the overflow or the underflow of the DMC respectively.
F_B	A buoyancy force acting on a single particle.
F_E	External forces such as gravity or centrifugal forces acting on a particle.
F_S	Shear drag forces acting on a particle due to fluid viscosity.
F_P	Forces acting on a particle due to pressure gradients in the fluid.
F_A	The acceleration force of a single particle in a fluid.
d	Diameter of the spherical particle.
ρ_p	Density of a particle.
π	Pi – a mathematical constant approximately 3.14.
a_p	Acceleration of a particle.
U_p	Velocity of a particle.
r_p	Radius of a particle.
μ	Viscosity.
U	The velocity of a particle relative to a fluid.
ρ_f	Density of a fluid.
Re_p	Reynold’s number of a single particle.

C_D	Drag coefficient.
S_U	Dense medium split designated to the DMC underflow.
D_{50}^{*}	RD cutpoint of an infinitely large particle separated in a medium producing a shear drag force of zero.
R^2	Statistical measure for model fit or coefficient of determination.
β	Neural network learning rate.
τ	Time constant.

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CHAPTER 1

INTRODUCTION

For the six months ended June 30 2010, Exxaro saw a 10% increase in total revenue. For the same period, Exxaro delivered 29% more coking coal to the domestic market. According to a mining weekly article published on the 20th of August 2010 "one can assume that it (29% more coking coal delivered into local market) was a significant" contribution to the 10% revenue increase for the six months ended (Faurie, 2010). This noticeable increase in coking coal supply to the local market was due to some complication at the Richards Bay Coal Terminal, responsible for coking coal export. Exxaro's financial director Wim de Klerk added, "should the situation remain the same, this could mean that Exxaro would *further* increase its revenue generated from coking coal supplied to the local market" (Faurie, 2010).

This is the current position of the coking coal supply section of the JSE listed company Exxaro. An increase in the demand for coking coal introduces a higher coking coal supply order. One of Exxaro's open-pit mines, is a world-renowned coal beneficiation site, and is responsible for 1.1 Mtpa production of coking coal (Exxaro Coal, 2009). It is at one of this site's beneficiation plants, GG1, where a manual quality control on coking coal has been implemented.

As mentioned in the article, Exxaro is now in an agreement with ArcelorMittal South Africa (AMSA) to supply coking coal at an increased price. AMSA is a steel manufacturing company utilising coking coal from Exxaro's world renowned coal beneficiation site, GG, in their production of steel. Coking coal is used in the coke making process, producing nearly pure carbon utilised in a blast furnace for iron making. The coke ovens are responsible for driving off impurities from coking coal in the coke making section. Coal impurities (proportional to the ash content and thus the quality of the ash) are unfavourable for the ovens. Coal impurities also have a negative effect on the coke production rate (Çoban, 1991). Thus, coking coal quality is an important attribute to a client like AMSA. It is therefore in Exxaro's interest to produce the stable quality coking coal demanded by the client.

From the information gathered from multiple sources, including GG1 metallurgists, engineers and relevant documentation, the main issue identified was the inefficient quality control on the 10.3% ash semi-soft coal product at GG1, leading to some stockpiles not achieving an average ash content of 10.3%. The loss of good quality coal due to fluctuations in the average ash accumulation of the coking coal delivery is also another disadvantage of this inefficient quality control. As discussed in chapter 2, the SBS is responsible for numerous calculations and visual representation of the calculated results. The SBS gives percentage ash content as an output to the operator and the operator is then responsible for the quality control of the semi-soft coking coal stockpile (10.3% ash average). The operator uses manual control to adjust the separation RD of the magnetite suspension introduced to the DMCs situated in the five modules.

Section 4.2 discusses the task discovery process for this investigation. The task discovery process is part of the knowledge discovery process that provides the necessary structure to the study. The objectives identified in chapter 4 are discussed in this introductory chapter to give context to the study.

1.1 OBJECTIVES

The purpose of the research is to investigate the benefits of an optimised manual control of the separation relative densities of the dense medium in the five modules located in AREA 04. This is accomplished combining the necessary knowledge gained from a KD process and process background studies to simulate the process using an accurate process model and effectively optimise the target variable to the operator for better quality control. A neural network (NN) will be used to model the process and a genetic algorithm (GA) will be responsible for the optimisation of the set points provided to the operator. The purpose of the solution developed in this investigation is not for implementation at GG1 but rather for investigating the possibility of an optimised manual control strategy using the data available from the process. Furthermore, the possible benefits of an optimised control strategy are analysed. Figure 1 illustrates the objective of the optimisation solution investigated. The aim is to decrease the variance in the ash content distribution in the final coal product. In addition, each stockpile stacked should contain predefined average ash content, usually 10.3% ash (Rautenbach, 2009a).

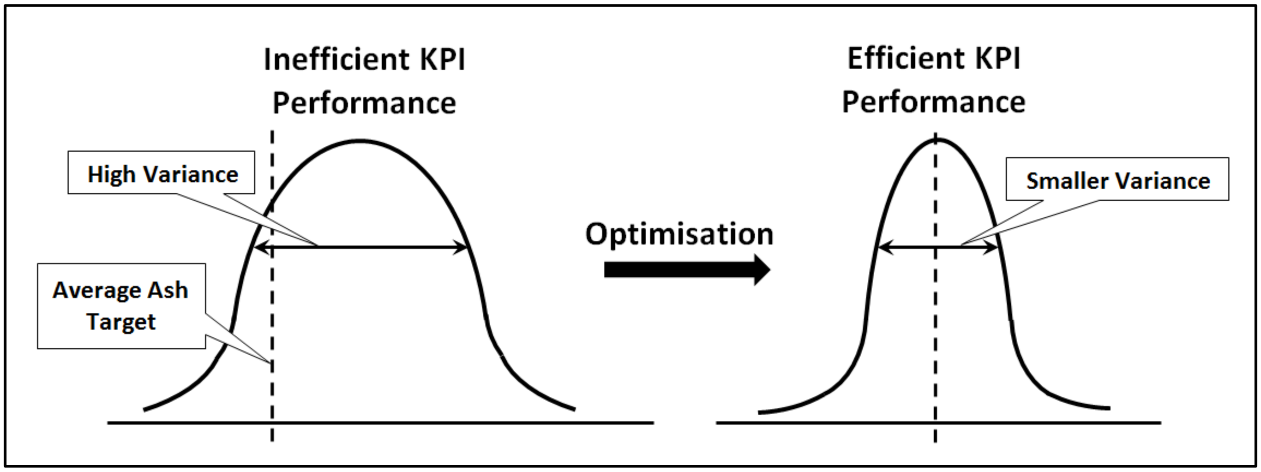

Figure 1: Optimisation objective

1.2 INVESTIGATION APPROACH

The optimisation solution approach for the DMC beneficiation area at GG1 is illustrated in figure 2. The knowledge discovery process is a well-suited investigation structure. The objectives of the study are incorporated into the KD process. The structure of the study is listed below.

1. Data and task discovery (chapter 4): Defining the problem statement, project objective, and discovering and extraction of the relevant data.
2. Data pre-processing (chapter 5): At first, data transformation and integration entail the construction of a data warehouse from which the preceding steps will build on. The data summarisation and data cleaning involve introducing “clean”, representative data with high quality to the data mining stage.

3. Data mining (chapter 6): Involves the accurate modelling of the process on data representative of the process dynamics. This stage includes the training and evaluation of the model.
4. Process optimisation (chapter 7): Include generating the benefit estimation solution, conducting sensitivity analysis for optimal quality control simulations, and discussing the benefits for such an optimal quality control compared to the current control strategy.

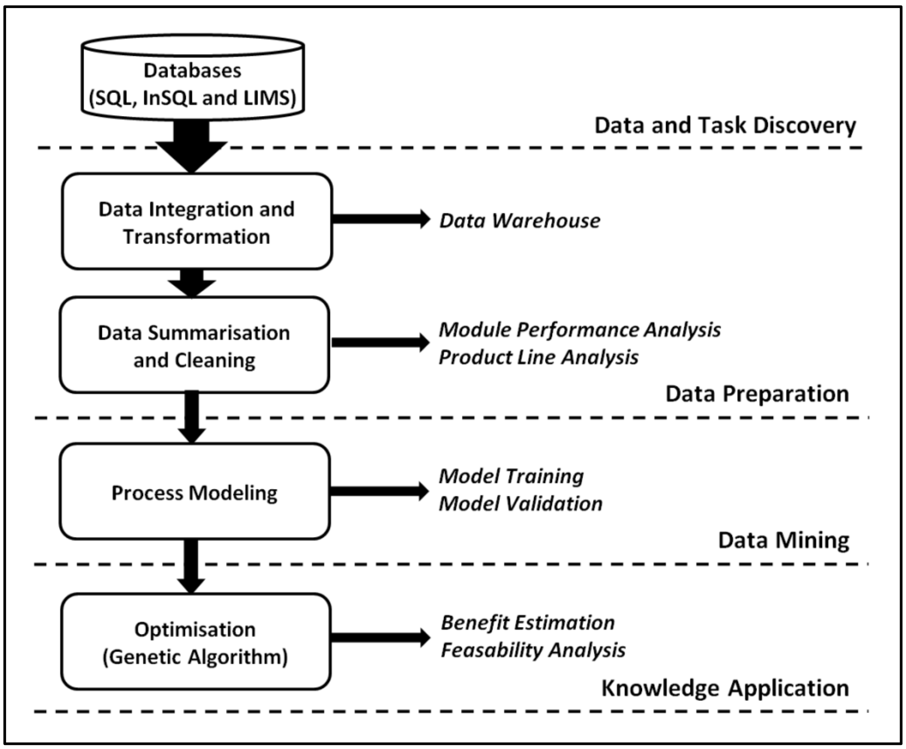

Figure 2: Optimisation solution approach for GG1 DMC beneficiation

1.3 MOTIVATION

Many characteristics of human activities have been fundamentally altered by the new age of the digital computer. At the same time, growing complexity of, for instance industrial manufacturing processes and competition on global markets impose increasingly greater demands for computational intelligence. These factors influence the way industries such as in the mining and manufacturing sector approach process automation and optimisation.

The growing complexity of industrial manufacturing processes and growing rate of the amount of data stored in different repositories are two of the main motivations for data driven optimisation. Continual process improvement and optimisation is an integral part of increasing revenues generated on production plants. Even the slightest improvements may benefit companies in the end. Continuous advancements and understanding of novel technologies and science could fill the gap between sub-optimal process performance and optimal revenue generation. This study underlines the need and value of an intelligent process optimisation approach on a coking coal quality.

CHAPTER 2

COAL PREPARATION

2.1 INTRODUCTION

The data generation domain in recent years has expanded at a rate faster than humans can absorb it. Nearly all the sectors of civilisation are generating masses of data. Yet, the full potential of the information discovery within these vast amounts of data has not been reached. In the industrial sector, thousands of data attributes stored in hundreds of data repository per industrial site are untouched when it comes to true knowledge discovery (Olson & Shi, 2007). This is the case of data relevant to the manual quality control of a coking coal stockpile at one of GG's coal beneficiation plants. A huge amount of data relevant to the problem environment is logged, yet the quality control on the coking coal stockpile has room for improvement as shown in this study.

As proven in this background study coal is responsible for more than half of South Africa's electricity generation. Not to mention coal exports adding to coal's value for South Africa. It is therefore in any coal beneficiation plant's best interest to deliver on consumer needs as accurately and efficiently as possible. Cyclone quality control plays a central role in achieving these goals. This investigation focuses on extracting the necessary information from the data in order to simulate dense medium cyclone (DMC) process behaviour and applying the extracted data knowledge to the optimisation of the quality control at GG1.For meaningful investigation, chapter 2 is dedicated to give more background on the problem environment at GG1.

2.2 COAL PREPARATION

The main objective of a coal preparation (beneficiation) plant is the extraction of valuable qualities from run-of-mine (ROM) coal at optimal efficiency, at the lowest cost, with the proper consideration for the impact on the environment, and meeting the client's product specifications. The chain of events in extracting the valuable coal properties includes the exploration of a colliery site, the mining and extraction of the coal from ROM, the handling and stockpiling of treated coal, crushing, screening, and beneficiation. In the process of achieving the objective, mined coal from coal seams in the earth's crust undergoes different levels of cleaning. Since no two coals are the same due to variability in coalification conditions, the preparation levels parameters from ROM coal to valuable coal for the client, differ from site to site. However, the beneficiation principles stay the same, implying the removal of impurities and unwanted materials, and coal size reduction for more intense and effective coal "washing" in order to increase the quality of the coal (Horsfall, 1993).

2.2.1 ORIGIN AND FORMATION

Coal, a non-renewable energy source, is the most abundant fossil fuel on earth. This organic rock is a heterogeneous mixture of organic and inorganic material, originating from the alteration of peat. Under suitable conditions, thick layers of plant remains were covered with sediment over the years causing the coalification. The chemical activity of bacteria and fungi is responsible for the first stage of coal formation where these layers of plant material undergo a biochemical process to form peat. Due to proper pressure, heat, time and other physical phenomena, the second stage of the alteration of the original plant material takes place as the coalification stage. Coal, as a solid fossil fuel, is generally found in stratified depositions because of the original layers of peat (England *et al*., 2002).

The quality of the coal ultimately depends on the degree of peat metamorphoses. The degree of metamorphoses (coalification) in turn depends on the conditions under which the coal was formed. These conditions include pressure, geothermal heat, time, oxygen supply and other physical phenomena such as volcanic activities. The conditions where coalification takes place vary from area to area. Thus, no two coals are ever the same (Perry, 1997).

With time, the coalification process brings about several coal formation stages. Each stage holds a certain coal quality range recovered in specific beneficiation processes.

Peat is the first stage of the coalification process. This product has very little value. Lignite or brown coal differs from peat in the moisture content. Lignite is less moist than peat as lignite suffers harsher coalification conditions. Coal, buried deeper in the earth experiences more intense geothermal temperatures, pressures and lower oxygen supply. In these conditions the volatile matter (a measurement of the quality of coal) decreases producing a higher quality coal. Bituminous and finally anthracite are the higher and highest quality coals respectively, with the lowest volatile matter content (England *et al.*, 2001).

The strata of the South African coalfields are horizontal and hardly ever surpass a slope of five degrees. Any disturbance in the horizontal seam characteristic in coalfields is more than often a result of igneous activity or earth movement that disturbed the horizontal beds during coalification (England *et al*., 2002).

2.2.2 COAL PROPERTY PARAMETERS

The analysis of coal properties serves as the crucial information for any application or area relating to coal. An example of analysis application is for insight into market suitability where the following parameter set is of importance: ash content; heat value; volatile and sulphur content, and elemental components. Continuous analysis of coal is imperative for the proper control of collieries and preparation plants. Some beneficiation complexes make use of their own laboratories for more rapid data analysis, while some companies prefer the use of commercial laboratories for more intricate analysis (Leonard, 1991).

The determination of inherent moisture content, ash content, fixed carbon, swelling number, calorific value and sulphur content is collectively referred to as general analysis. The most commonly used analysis in identifying specific coals for specific utilisation is the proximate analysis where the moisture content, ash content and volatile matter with fixed carbon, determined as the difference out of a 100, are determined as weight percentages (England *et al*., 2002).

2.2.2.1 MOISTURE CONTENT

Moisture appears on the surface of the coal as free or surface moisture and in the internal pores of the coal as inherent moisture. The moisture content is an unwanted constituent of coal and decreases the coal's calorific value, ultimately lowering the coal quality. The vacuum-oven method is a SABS standard for determining the moisture content in coal samples (SANS 5924:2009). Several dewatering techniques are available to reduce the free moisture content of the coal. Inherent moisture, however, cannot be removed by conventional dewatering methods, but can be removed by heating the coal above the moisture's boiling point (England *et al*., 2002).

2.2.2.2 ASH CONTENT

The ash content of coal is the weight of the residue after complete incineration of coal under certain testing conditions (ISO 1171:1997). The residue content represents the mineral impurities within the coal. The amount of residue is inversely proportional to the heating value of the coal and thus to the quality of the coal. As the ash content increases, the quality of the coal decreases.

The presence of mineral components in coals is most probably due to inorganic rocks in adjacent strata penetrating coal seams during or after coal formation or during coal mining. Mineral impurities include minerals containing elements such as silicon, iron, calcium, magnesium, and sulphur. The mineral content of coals differs from site to site, depending on the different conditions of coalification (Liu *et al.,* 2007).

2.2.2.3 CALORIFIC VALUE

Calorific value or heating value is the "measure of heat produced from a unit weight of coal" (Leonard, 1991:884). Two bomb calorimeter methods of calculating the heating value are available: static isothermal method and adiabatic method. The static isothermal method is not common and makes use of a 'thermal jacket' surrounding the bomb. The ISO 1928:2009 standard describes the method of determining the calorific value in adiabatic conditions. This property is a crucial indicator in the classification and specification of coal (England *et al*., 2002).

2.2.2.4 SPECIFIC GRAVITY (RELATIVE DENSITY)

The specific gravity of coals is a crucial property to the coal preparation technology in use today. Specific gravity is the density of a substance relative to the density of a reference substance at a specific condition, usually water at 4°C (Felder & Rousseau, 2000). The definition given for relative density relates to the specific gravity definition (England *et al*., 2002). Relative density (RD) will be used in the remainder of this document.

The RD range of coals lies between 1.23 and 1.72, depending on three parameters: the rank of the coal, the moisture content of the coal, and the ash content. In theory, the quality of a coal increases with a decrease of the coal RD. For a specific coal rank, the increase in the percentage ash content leads to an increase of the coal's RD (Leonard, 1991). The cleaning or "washing" of the coal at a particular RD facilitates the control of the ash content of the washed coal (England *et al*., 2002).

RD is the key component in the evaluation of the washability characteristics of coal. The float-and-sink analysis is responsible for generating washability curves used to describe the washability of coals, evaluating the efficiency of separators and effective plant control (England *et al*., 2002). These evaluation methods are described in more detail in section 2.3.

2.2.3 COAL UTILISATION

As mentioned, the chief objective of a coal preparation plant is to produce a coal product in compliance with the consumer utilisation criteria to gain the maximum profit. In order to achieve this goal and generate the greatest possible profit, the utilisation of the "cleaned" coal must reach its full potential. The rank of the coal is the determining factor in sorting the "cleaned" coal produced at the preparation plant into the proper utilisation category. Great financial loss comes from not sorting the prepared coal into the correct utilisation categories. The origin of this unrealised potential is at the source of coal production: the coal seams. Coal seams are not homogeneous but highly heterogeneous. Effective preparation for heterogeneous coal feeds to be separated into multiple coal products is essential.

A parameter influencing the sorting of the cleaned coals into the different utilisation categories, is the ability to meet the government regulations. Restrictions such as the sulphur content limit and the carbon dioxide emission regulations restrict coal preparation to some extent. These regulations are dependent on the dynamicity of political and public demands. In order to meet the demands of the regulations and to deliver the highest quality product, several trade-offs between quality and consumer demand are compulsory (Leonard, 1991).

2.2.3.1 SOUTH AFRICAN COAL CHARACTERISTICS

South Africa's coal industry compares very well to the international coal industry. South Africa is ranked the fifth largest coal producer in the world (Van Wyk *et al.,* 2006). The total ROM coal production in South Africa in 2006 was 312.5 million tonnes, of which 245 million tonnes were of saleable quality. Figure 3 and figure 4 clearly indicate the South African coal industry as a highly concentrated coal production industry. The top five coal producing companies (including Exxaro) account for almost 90% of the ROM coal production in South Africa. The Waterberg coalfields were responsible for 36 million tonnes of coal produced in 2006.

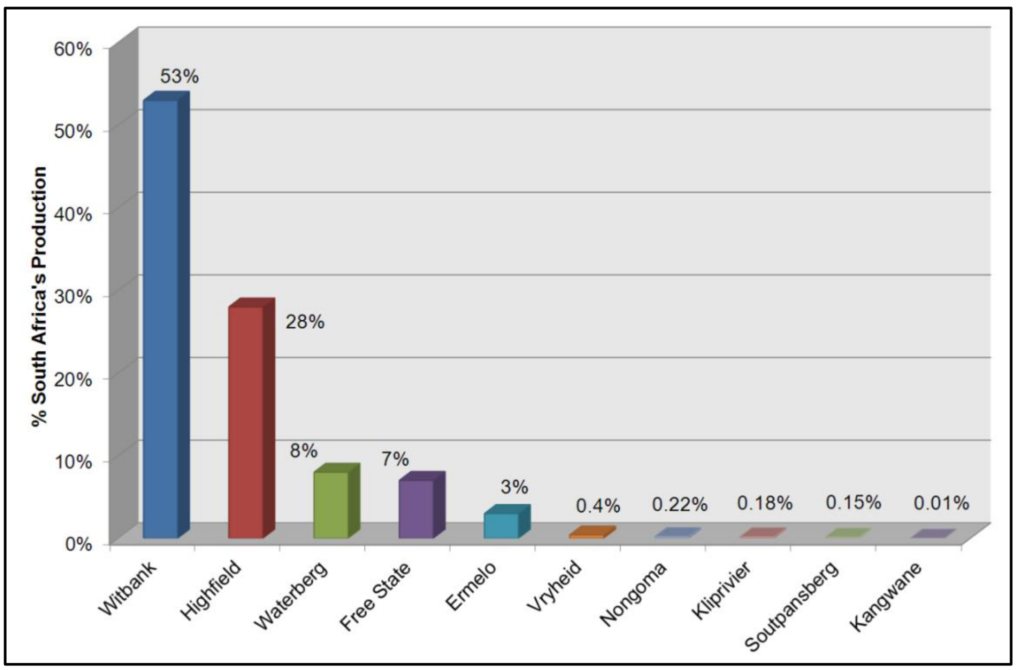

Figure 3: Coalfields ROM production in 2006 (U.S., 2009)

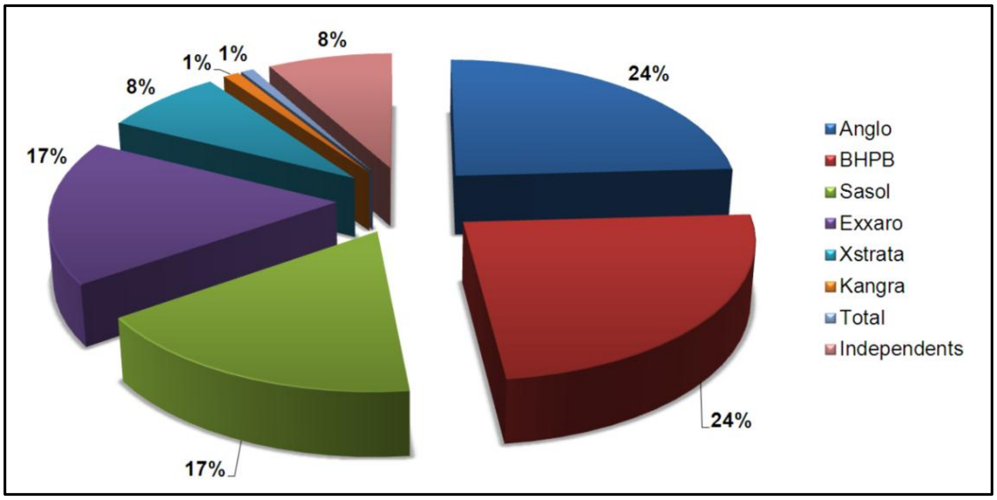

Figure 4: Coal production by mining company in 2006 (U.S., 2009)

The most commonly used primary fuel in the world is coal. Coal provides 68% of the primary energy needs in South Africa (South Africa, 2009). Figure 5 indicates the dominating nature of coal in the energy sector.

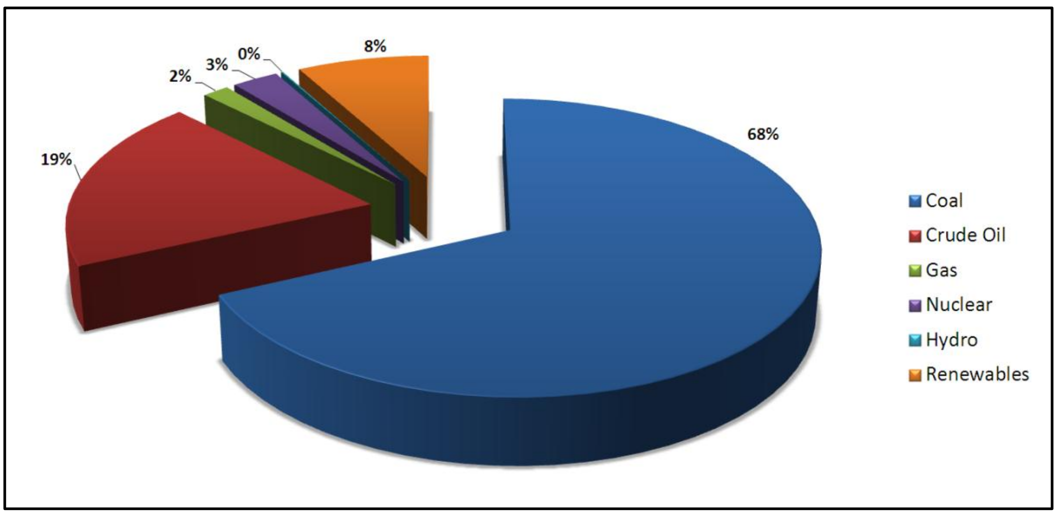

Figure 5: Primary energy sources for South Africa in 2004 (Van Wyk *et al*.., 2006)

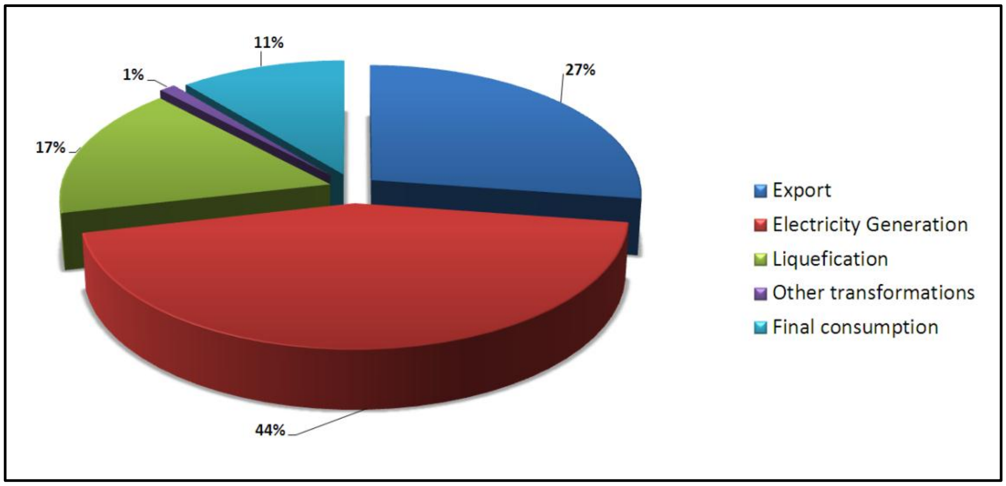

Figure 6: Coal utilisation in South Africa for 2004 (Van Wyk *et al*.., 2006)

Figure 6 is a clear indication of the high coal utilisation in the energy sector. Coal trading abroad accounts for 27% of the coal utilisation. As the production of coal increased, the demand for coal also increased over the years. Figure 7 illustrates the trends of this increase in consumption of coal in its different forms of utilisation. Eskom is responsible for 97.5% of the total coal consumption used to generate electricity. Other coal consumption areas illustrated in figure 7 include consumption in town gas, merchants and domestic consumption, and industrial consumption. Coking coal used in the iron and steel industry also shows relatively high coal consumption.

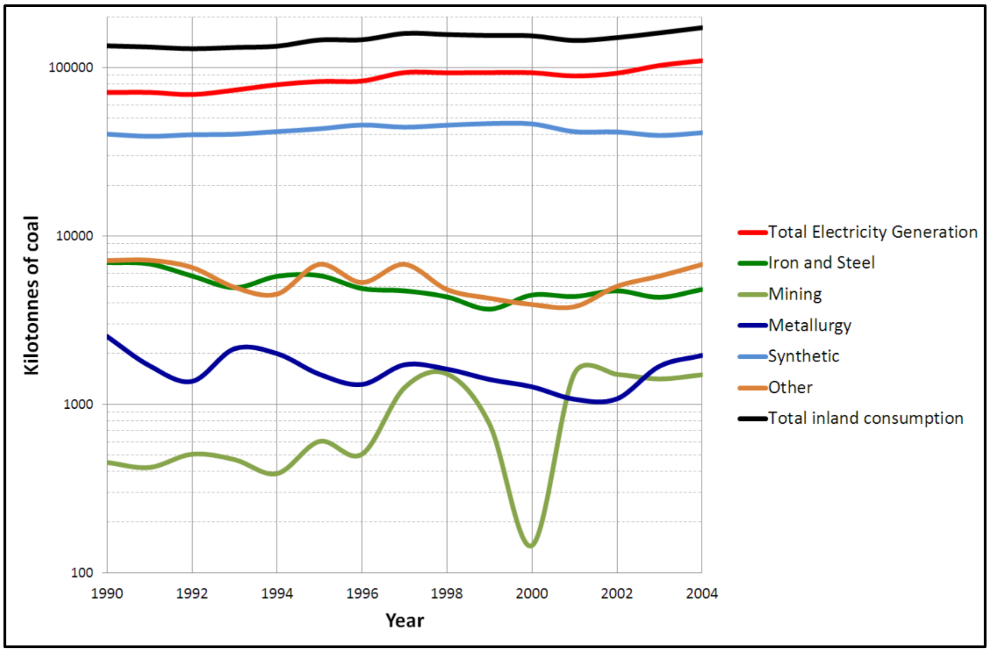

Figure 7: Historical consumption of coal in South Africa (Van Wyk *et al*.., 2006)

South Africa is a carbon-intensive economy and among the top twenty emitters of greenhouse gases (GHG). This country produces more or less 500 million tons of carbon dioxide equivalents per annum, more emissions than all other Sub-Saharan African (SSA) countries combined (as depicted in figure 8). Around 40% of the emissions are attributable to the export of carbon-intensive goods (Du Plooy & Jooste, 2011). In seeking to reduce domestic GHG emissions, South Africa aims to implement carbon tax into the 2012 budget (Creamer, 2011).

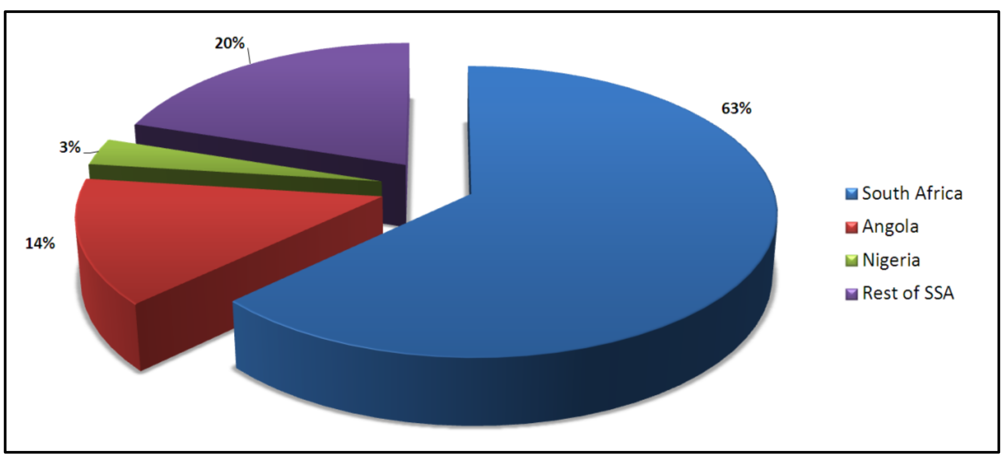

Figure 8: CO_2 emissions from energy use per annum (Du Plooy & Jooste, 2011)

The purpose for carbon tax in South Africa is to reduce the GHG emissions according to a study done on the economic implications of carbon tax (Winkler & Marquard, 2009). Two main effects of carbon tax on the economy are the decrease in energy demand due to higher prices as well as to less intensive fuels. In concluding their study, Winkler and Jooste proposed that the government's main consideration in insuring South Africa competes in the climate-friendly and low-carbon world should be carbon tax. However, considering carbon tax in lowering GHG emissions, the government should still meet certain socio-economic objectives. According to Creamer, the National Treasury is also drawing attention to job creation, economic competitiveness as well as poverty reduction in considering carbon tax in 2012's budget. Carbon tax will have a significant influence on the coal mining and processing industry.

2.3 COAL PREPARATION PROCESS DESCRIPTION

As mentioned, the main goal of most of the coal beneficiation plants is to separate the ash-forming materials from the combustible materials. Gravity concentration is the core unit operation of most coal washing plants (Majumder, Barnwal, Ramakrishnan, 2010). For this reason, it is imperative to identify and continuously monitor the efficiency of the DMS units as well as the operation performance of the DMS units for accurate quality control.

2.3.1 DENSE MEDIUM SEPARATION

DMS is the separation of clean coal particles from discard exposing the density distribution of the coal feed to a dense medium with a specific separation RD. Floating material will typically contain more coal than the discarded sinks when immersed in the dense medium. The particles with the higher specific gravity will sink and the particles with lower specific gravity will float (Perry, 1997).

The degree of gravity separation depends partially on the liberation of the particle with different densities. The more the particles with differing RDs are detached from each other, the higher the yield of the wanted product from the process. This process is illustrated in the liberation of the particles lies in the breaking and grading of the material. However, with the liberation comes the trade-off between higher separation efficiency by liberation or higher capital cost in the separation of fine particles (Perry, 1997).

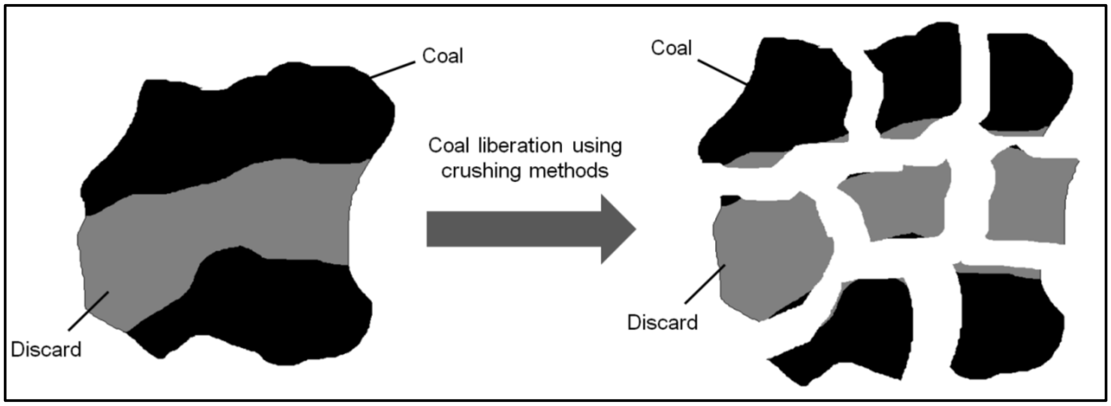

Figure 9: Coal liberation (De Korte, 2009b)

Several DMS units are available for coal beneficiation and can be categorised into two groups: gravitational separators and centrifugal separators. Gravitational separating vessels depend on the removal of floats via paddles or vessel overflow. The feed introduced to the vessel contains the separation dense medium as well as the material to be separated. Denser particles separate from lighter particles (also known as the floats). The floats exit the vessel via overflow while the rest of the contents in the vessel are slowly agitated in order to keep the medium in suspension. Centrifugal vessels are the more widely used DMS units. High centrifugal forces in the vessel enable the effective separation of lighter particles (good quality particles) from heavier particles (Wills &Napier-Munn, 2002). The DMC operation is the focus of this literature study.

2.3.1.1 MAGNETITE AS DENSE MEDIUM

In 1912, T.M. Chance from the USA came to realise that solids suspended in a liquid could replace liquid solutions in dense medium washing. He used sand suspended in water to replace expensive and often poisonous liquid solutions. In the 1950s, magnetite was introduced to DMS as solid suspended in water. Magnetite in water suspensions are the most often used dense medium for DMS operations (Horsfall, 1993).

The composition of the dense medium is an important property criterion to which the dense medium is evaluated. A dense medium suspension composition contaminated with shale or other unwanted materials should be limited or if possible avoided, since the RD of the dense medium is reliant on the density proportion of each component of the suspension. Unwanted constituents lower the RD resulting in the forced addition of more medium solids contributing to unwanted expenses, increasing the medium viscosity and ultimately decreasing the efficiency of the dense medium. In the case of a high viscosity, the medium becomes too thick for efficient density separation. Particles suspended in a dense medium with high viscosity take longer to separate. The inefficiency results in unwanted heavier particles reporting to the floats. The medium particle size also plays a crucial role in the stability of the medium. Coarser solids tend to settle out more readily, consequently destabilising the medium. Finer medium in a dense medium is more stable, but increases the viscosity of the medium (England *et al.*, 2002).

Magnetite suspended mediums offer high resistance to attrition, suitable for a wide range of separation densities. Effective separation and high magnetite recovery is achieved using magnetic methods (Perry, 1997). The magnetite solids also do not degrade giving this medium the advantage of not altering its properties with time. Ferro-silicon is also a solid appropriate for use in DMS. However, this medium tends to be more prone to corrosion than magnetite suspensions (Du Plessis, 2009).

Fine non-magnetite solids tend to elude screening operations of coal and are responsible for the build-up of unwanted contaminants in the dense medium suspension. It is therefore vital for a coal beneficiation plant to have a dense medium recovery and concentration system in place to eliminate the build-up of contaminants in the suspension. This recovery and concentration system is also responsible for the concentration of a dilute medium produced after washing the coal with water (discussed below). Common to these recovery systems is the integrated tank-level control system able to regulate the RD of the dense medium (England *et al.*, 2002).

There is not one recovery system able to adhere to all coal beneficiation constraints for ideal dense medium recovery and concentration; however, some common principles are discussed below (Osborne, 1988).

Figure 11 is a process flow diagram of a typical magnetite recovery and concentration system for a coal beneficiation area using DMC separation units. Raw coal enters the DMC beneficiation area via a conveyor, transporting the raw material to a degradation screen. In the case of each of the five beneficiation modules in AREA 04 at GG1 (Exxaro), the screens are responsible for separating the -1mm fines (undersize) from the oversize coal (+1mm – 25mm). The oversize is fed to a mixing box responsible for mixing the coal and the dense medium[1]. The magnetite suspension entering the mixing box is at the controlled separation RD and will be referred to as the correct medium, as indicated in figure 11. The correct medium is pumped from a correct medium storage tank to the mixing box.

At GG1's AREA 04, two DMCs are responsible for the separation of the floats[2], designated for the semi-soft coking coal stockpile, and the sinks[3], designated for the power station coal stockpile. A splitter box is in charge of dividing the coal and dense medium feed stream to the DMCs, equally. The correct medium is recovered after DMS separation, using desliming and drain-screens. Unrecovered correct medium is rinsed with water and drained on the screens (as indicated in figure 11) to a dilute medium. The dilute medium resides in the dilute medium tank and the correct medium in the correct medium tank.

Ferromagnetic characteristics of magnetite facilitate high medium recovery and simplify the control of the recovery and concentration system (Osborne, 1988). Rapid magnetic drum separators are used in AREA 04 to separate the magnetite from the water and from non-magnetic contaminants. As illustrated in figure 11, pumped dilute medium enters a splitter box responsible for dividing the feed into equal streams designated as

[1]The dense medium used at GG1 is a magnetite suspension.
[2]The floats in this area ideally should correspond to a coal ash quality lower than the separation density.
[3]The sinks in this area ideally should correspond to a coal ash quality higher than the separation density.

feed streams to the magnetic drum separator. Figure 10 illustrates the operation of a magnetic drum separator. The dilute medium enters the separator in a trough keeping the suspension in contact with the lower point (feed pan gap) of a rotating magnetic drum. Magnets are fixed at the bottom of the drum and do not rotate along with the drum. These magnets create an intense magnetic field drawing the magnetite particles out of the suspension to the “discharge zone”. The drum rotates until the particles leave the magnetic field and fall into an exit trough, transporting a high concentration magnetite stream called the “overdense medium” stream (indicated as the “magnetite concentrate” in figure 10). The overdense medium stream is sent back to the correct medium tank through a demagnetiser. The purpose of the demagnetising coil is to demagnetise the magnetite retaining magnetism when emerging from the magnetic drum separator. Magnetic magnetite particles agglomerate and tend to settle out, preventing the particles to disperse in the suspension. From the magnetic drum separator the effluent suspension containing non-magnetic contaminants and water is sent to a water clarifying section as tailings (England *et al.*, 2002).

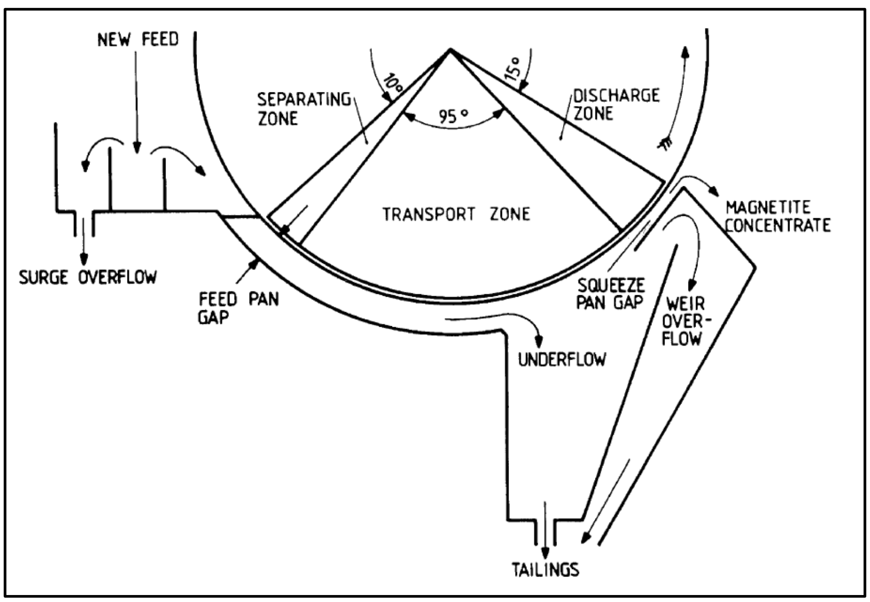

Figure 10: Magnetic drum separator flow schema (Rayner & Napier-Munn, 2003)

The RD of the magnetite suspension determines the degree of separation in the DMCs located in the secondary beneficiation area at GG1. Thus, the correct medium density is vital to the quality control philosophy of the AREA04 products at GG1. For the accurate control of the level in the medium tanks to prevent tank overflow, a constant density of the correct medium and the medium flow to respective destinations are imperative. This control should maximise magnetite recovery and optimise density control for more ideal separation.

AREA 04 uses nuclear density gauges to measure the density of the correct medium (as indicated in figure 11). In decreasing the density of the medium for regulatory purposes or in case of a RD set point decrease, the medium is simply diluted by the addition of water. This addition of water for medium dilution may take place by either adding water directly to the correct medium line[4] to the mixing box, or adding the water to the correct medium tank. The density control should compensate for effect the overdense medium has on the RD in the correct medium tank, given that the high concentration of the stream increases the density within the tank.

A distribution box situated between the medium tanks and the overflow is responsible for the tank level control. The box bleeds off some of the correct medium to the dilute medium tank in order to control the levels in the tanks. In the case of an increase in the set point of the relative density, more correct medium are bled to the dilute medium tank in order to produce a higher overdense stream from the magnetic separators. The increase in the overdense medium increases the RD in the correct medium tank. The process in increasing the relative density of the correct medium is responsible for a time lag from the time the operator increases the set point to the time the relative density reaches the specified value. The lag in the increase of the density is much longer than decreasing the density.

An analysis study done on the medium losses at a coal beneficiation plant in India, also describes the control of the plant with the use of PID (proportional, integral, and derivative) controller. The level of the dilute medium tank is controlled using the distribution box as control element (Sripriya, Dutta, Dhall, Narasimha, Kumar, Tiwari, 2006).

[4]This alternative addition of water is indicated with the red water line in Figure 11.

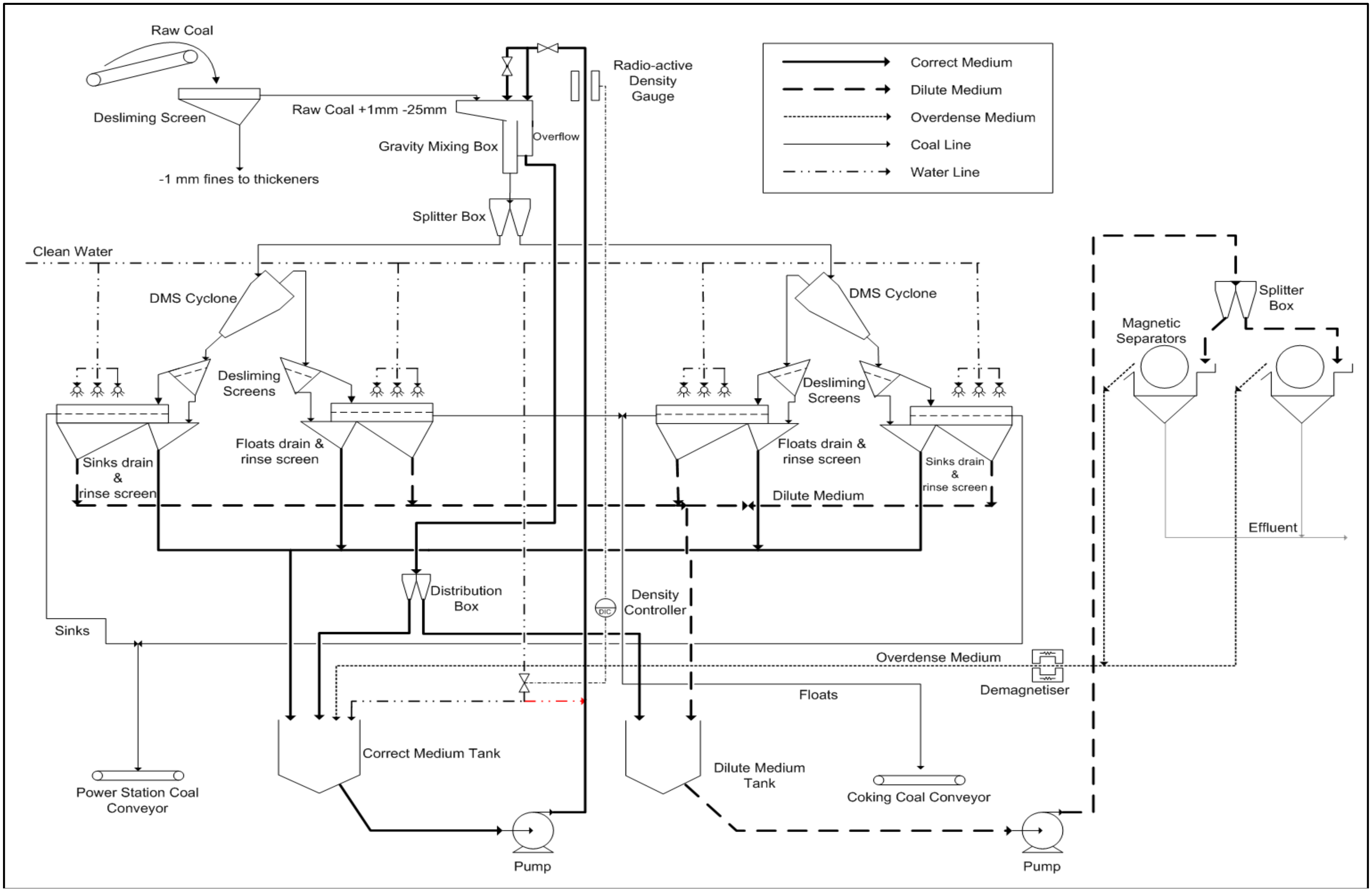

Figure 11: Magnetite recovery and concentration system (England *et al*., 2002; Osborne, 1988)

A loss in dense medium during DMS operation contributes to high operating costs. According to a study done on medium losses at coal washing plants (Sripriya *et al,.* 2006), 10% – 20% of operating costs are attributable to magnetite loss during operation. Adhesion to coal material after draining and rinsing screens as well as magnetic separation process inefficiency are normally the two main contributors to magnetite loss (Sripriya *et al,.* 2006).

Adhesion losses after draining and rinsing are mainly due to loading increases on the screens. In the investigation conducted by Sripriya *et al.,* the medium spilt ratio[5] had a significant effect on magnetite recovery. If more magnetite reports to the floats, an increase in adhesion loss will occur at the floats drain and rinse screens. The effects of a change in RD versus an adjustment in DMC spigot diameter had on the medium split ratio were investigated. A change in medium RD had little influence on the medium split ratio and hence negligible effect on medium losses. On the other hand, increasing or decreasing the spigot diameter had a great influence on the medium split ratio (Sripriya *et al,.* 2006).

As for medium losses through magnetic separators, the investigation led to the conclusion that these losses are not a dominant source of medium loss. Medium losses through magnetic separators are more attributable to ineffective operation of the separators than to other factors. Magnetic separators appear to contribute 20% – 40% of the medium losses on the coal beneficiation plant, according to Sripriya *et al.*

2.3.2 DMS EFFICIENCY

2.3.2.1 FLOAT AND SINK ANALYSIS

Heavy liquid laboratory tests, called float and sink analysis (ISO 7936:1992), are responsible for determining the economic separating density for a particular coal recovery. Typical heavy liquids used during float and sink analysis is zinc chloride,

[5] The medium split ratio of a DMC refers to the magnetite fraction included in the floats relative to the magnetite fraction included in the sinks.

bromoform, tetra bromo ethane (De Korte, 2009b). As illustrated in the picture below, liquids with a range of densities are prepared for incremental test steps.

At the start of the test, a sample of coal is introduced into the liquid with the highest relative density. Adequate amount of time is needed for the particles with a higher density than that of the liquid to settle out to the sinks zone. After proper separation, the floats (particles with a lower RD) are removed, washed and introduced to the second liquid with a lower RD than the first. The floats from the second separation is removed after appropriate settling time and introduced to the third step and so on (Wills &Napier-Munn, 2006). The RD range for coal typically ranges from 1.30 to 1.70 with density intervals of 0.02 (England *et al*, 2002).

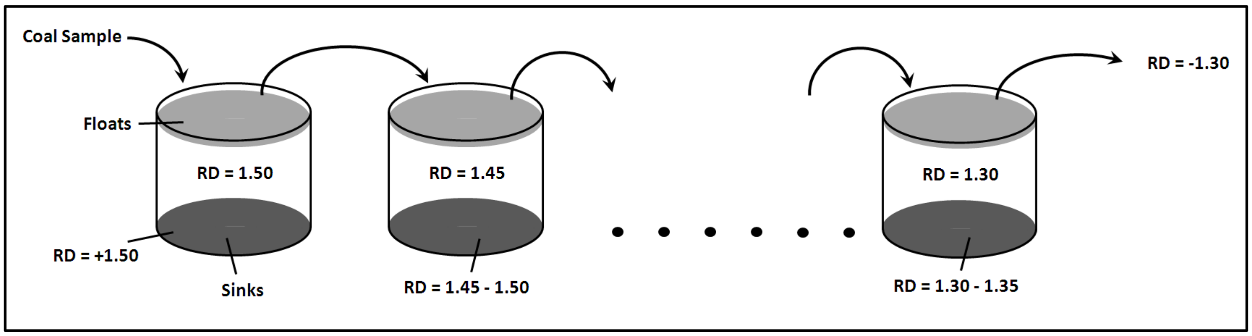

Figure 12: Float and sink analysis

The sinks of each step as well as the floats of the final step is drained, washed, and dried. Each incremental product is weighed and the ash content is determined to give a density and ash distribution of the coal sample by weight. This is a steady-state analysis because of the time required for the particles to separate sufficiently.

The assay results can be tabulated as shown in table 1. The density fractions from the incremental step test are shown in column (*a*). The fractions of the total sample weight for each incremental step are listed in column (*b*) and the ash content per fraction in column (*c*). Evident from the table is the ash content increase with the increase in RD. The ash product in each density fraction is calculated multiplying weight percentage with the ash content (column (*b*) multiplied with column (*c*)).

Table 1: Float and sink analysis results (Wills, Napier-Munn, 2006)

(*a*) RD Fraction	(*b*) Wt%	(*c*) Ash%	($d = b \times c$) Ash product	(*e*) Separation density	($f = \sum b_i$) Cumulative Float (Clean Coal) Yield%	($g = \sum d_i$) Ash product	($h = g/f$) Ash%
-1.30	0.77	4.4	3.39	1.30	0.77	3.39	4.4
1.30 - 1.32	0.73	5.6	4.09	1.32	1.50	7.48	5.0
1.32 - 1.34	1.26	6.5	8.19	1.34	2.76	15.67	5.7
1.34 - 1.36	4.01	7.2	28.87	1.36	6.77	44.54	6.6
1.36 - 1.38	8.92	9.2	82.06	1.38	15.69	126.60	8.1
1.38 - 1.40	10.33	11.0	113.63	1.40	26.02	240.23	9.2
1.40 - 1.42	9.28	12.1	112.29	1.42	35.30	352.52	10.0
1.42 - 1.44	9.00	14.1	126.90	1.44	44.30	479.42	10.8
1.44 - 1.46	8.58	16.0	137.28	1.46	52.88	616.70	11.7
1.46 - 1.48	7.79	17.9	139.44	1.48	60.67	756.14	12.5
1.48 - 1.50	6.42	21.5	138.03	1.50	67.09	894.17	13.3
+1.50	32.91	40.2	1322.98	-	100.00	2217.15	22.2

From these results, the required separation density and the expected yield of the coal at the appropriate ash content can be calculated using washability curves. Column (*f*) shows the results from the yield calculation:

$$Yield = \frac{weight\ of\ coal\ floats\ product}{total\ feed\ weight} \times 100\% \,.$$

Equation 1

The cumulative ash (*h*) is calculated dividing column (*g*) with the percentage floats yield.

From the float and sink analysis results a washability curve is generated as shown in figure 13. As indicated in the figure, for an accumulated ash percentage of 10% from the float product, the heavy liquid (or dense medium) should have a separation RD of 1.42. At this RD, a 35% yield is attainable, given that the settling time was sufficient during the float sink analysis.

Coal washability curves are used for the design of coal beneficiation plants. From these curves, the optimum separation densities are identified for techno-economic evaluations in order to design the desired coal washing plant. Day-to-day plant control evaluation also utilise washability curves (De Korte, 2009b).

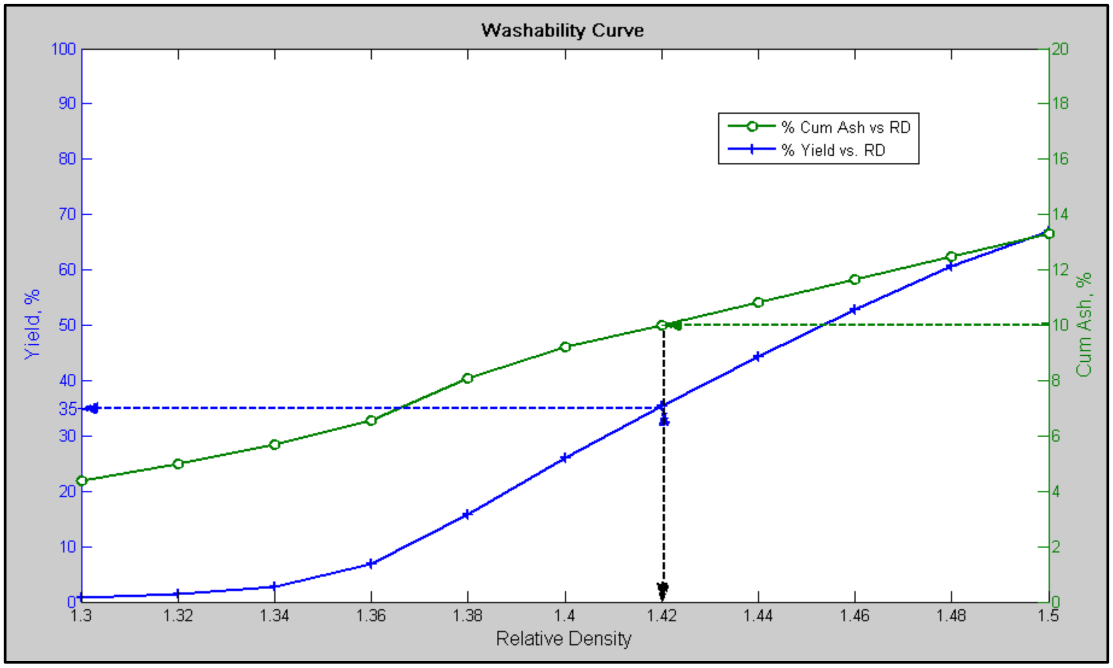

Figure 13: Washability Curve

DMS control performance is highly dependent on the weight percentage of the feed with a density close to the separation RD. The near-dense material is measured by the percentage of material with an RD of ± 0.1 from the separation RD. A coal sample with low amount of near-dense material but high amount of material outside of this RD range will separate more easily over a wide range of operating densities, than a high amount of near dense material. A small change in the separation density in the presence of a high weight percentage near-dense material, will certainly affect the operation performance of the DMS (Wills &Napier-Munn, 2006).

2.3.2.2 EFFICIENCY OF DMS

A high amount of near-dense material has greater odds of particles reporting to the wrong DMC outlet than low amount of near-dense material during normal operation. This is the case for continuous DMC production processes in contrast to the near ideal float and sinks laboratory analyses. Very light or very heavy particles tend to separate more rapidly than near-dense material. Because the near-dense material takes longer to separate in a DMC, material will end up in the wrong outlet. Therefore, a quantification of DMS efficiency is needed to investigate the degree of separation (Wills &Napier-Munn, 2006).

In constructing a partition curve (also called a Tromp curve), samples are taken from the overflow and the underflow of the DMC in operation. Heavy liquid tests discussed in the previous section are done on the samples in order to generate results as portrayed in table 2 (taken from England *et al.,* 2002). Columns (*a*) to (*d*) are results gathered from the float and sink analysis for each density fraction analysed. After enough time passed in which the density fraction products are dried, the sinks and floats material are weighed to determine the float and sink percentages of the feed (column (*c*) and (*d*) respectively). The nominal RD (column (*f*)) represents the RD range in a specific density fraction analysed. The partition coefficient is calculated as the ratio of the total clean coal to the feed.

Table 2: Partition curve data and calculations (Wills &Napier-Munn, 2006)

RD fraction	(*a*) Floats analysis (wt%)	(*b*) Sinks analysis (wt%)	(*c*) Floats% of feed	(*d*) Sinks% of feed	(*e = c + d*) Reconstituted Feed (%)	(*f*) Nominal RD	(*g = c/e*) Partition coefficient
-1.30	43.69	0.79	18.18	0.46	18.64	1.30	97.5
1.30 - 1.32	25.82	0.71	10.74	0.41	11.15	1.31	96.3
1.32 - 1.34	14.23	1.29	5.92	0.75	6.67	1.33	88.8
1.34 - 1.36	11.59	3.93	4.82	2.30	7.12	1.35	67.7
1.36 - 1.38	3.97	8.93	1.65	5.22	6.87	1.37	24.0
1.38 - 1.40	0.40	10.36	0.17	6.05	6.22	1.39	2.7
1.40 - 1.42	0.10	9.29	0.04	5.43	5.47	1.41	0.7
1.42 – 1.44	0.07	8.58	0.03	5.01	5.04	1.43	0.6
1.44 – 1.46	0.03	8.58	0.01	5.01	5.02	1.45	0.2
1.46 – 1.48	0.03	7.86	0.01	4.59	4.60	1.47	0.2
1.48 – 1.50	0.03	6.43	0.01	3.76	3.77	1.49	0.3
+ 1.50	0.03	33.24	0.01	19.41	19.42	1.50	0.05
Totals	100.00	100.00	82.60	17.40	100.00		

Figure 14 shows the partition coefficient relative to the RD of the heavy liquid used during the float and sink analysis as tabulated in table 2. The partition factor of 50%, or separation cut-point (D_{50}), is regarded as the effective density of separation. At D_{50} particles have an equal chance of reporting to either the overflow or the underflow of the DMC. The partition curve shows higher separation efficiency (separation of the clean coal from the discard) the further away the particles are from the separation cut-point (Wills & Napier-Munn, 2006).

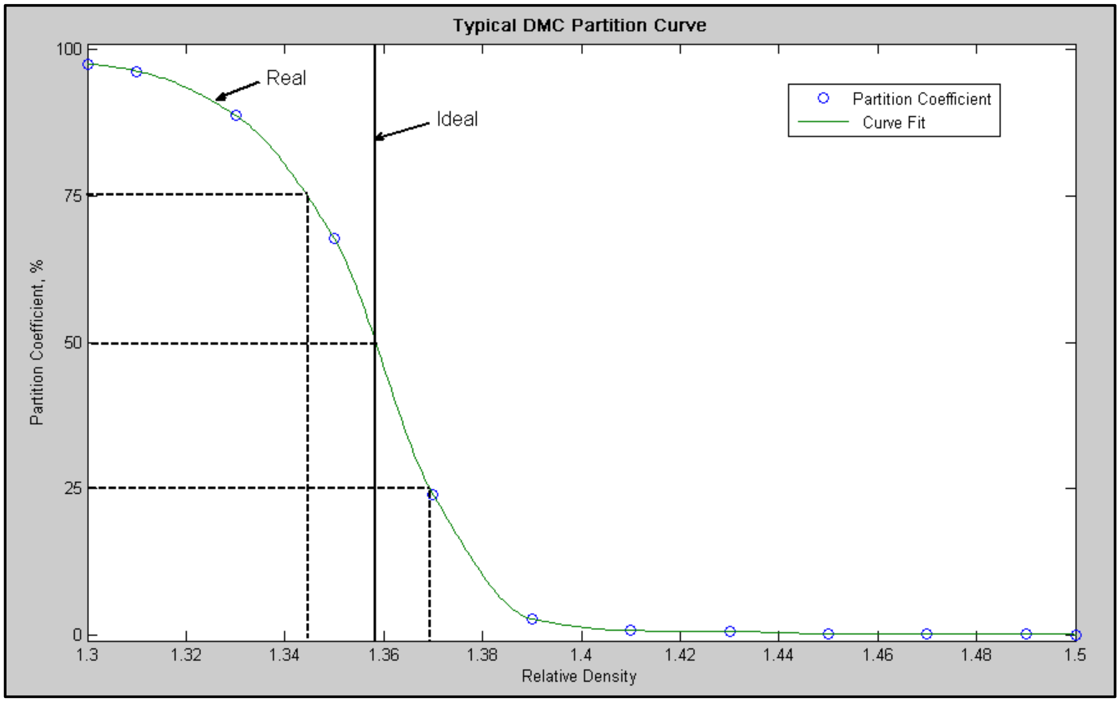

Figure 14: Partition curve example (England *et al.*, 2002)

As indicated in the figure, the partition profile of an ideal separation is a straight vertical curve indicating that all particles with a density higher than the separation density report to the sinks and the rest report to the floats. No material is misplaced in this scenario. However, in practice an error area exists when comparing the ideal to the real separation curve. A probable error of separation, also called the écart probable moyen (EPM), describes the slope of the curve between D_{75} and D_{25} and thus the extent of possible misplaced particles. The EPM is given by:

$$E_p = \frac{D_{25} - D_{75}}{2},$$

Equation 2

where D_{25} is the RD at a partition coefficient of 25% and D_{75} the RD corresponding to a partition coefficient of 75%. A low EPM indicates that the DMC achieves a good separation (Wills &Napier-Munn, 2002).

2.3.3 CYCLONE SEPARATION

In the 1940s, the Dutch State Mines introduced the DMC separation as a dynamic efficient separator unit since centrifugal force is applied in this separation process. DMCs typically treat a coal particle size range of 0.5mm – 40 mm. Some of the largest DMCs have diameters of one meter and are able to produce 250 tonnes per hour (Wills &Napier-Munn, 2002).

The magnetite medium is fed along with the coal feed at the top tangentially inlet of the DMC as illustrated in figure 15. The feed rate to the DMC is at such a velocity that a vortex is formed at the centre of the cone-shaped part of the DMC (figure 16). The particles with higher specific gravity than the separation medium, move to the inner cone wall of the unit and discharge at the apex (or spigot) situated at the bottom of the DMC (Horsfall, 1993). The particles with lower RDs move ('lifts') to the upper flow regime of the cyclone slurry in the cone. A vortex finder prevents short-circuiting within the DMC and carries the slow moving lighter particles to the overflow top orifice (Perry, 1997).

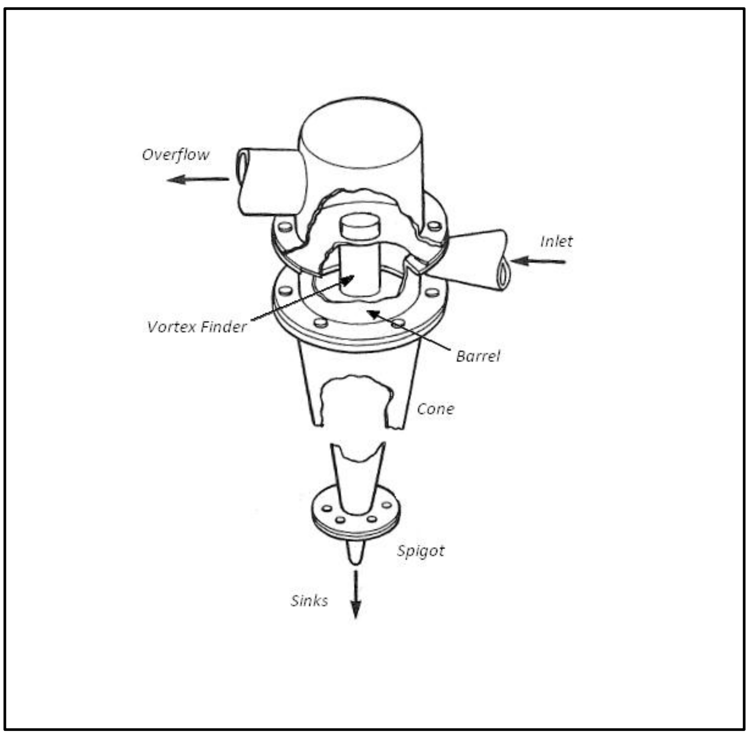

Figure 15: DMC Separator (Perry, 1997)

The efficiency of the DMC separator design depends on the coal particles size in the feed, the density of the medium depends on the degree of separation required, the cone angle, the sizes of the openings to the DMC (apex, inlet and overflow top orifice) and the pressure of the feed to the DMC (Perry, 1997). The feed pressure is achieved by either pumping the feed into the DMC at the proper pressure or the feed is first introduced into a head tank to obtain the necessary static head pressure. Pumps have the disadvantage of wearing out with time because of corroding nature of the feed slurry. The head tank, on the other hand, takes up much space (Horsfall, 1993).

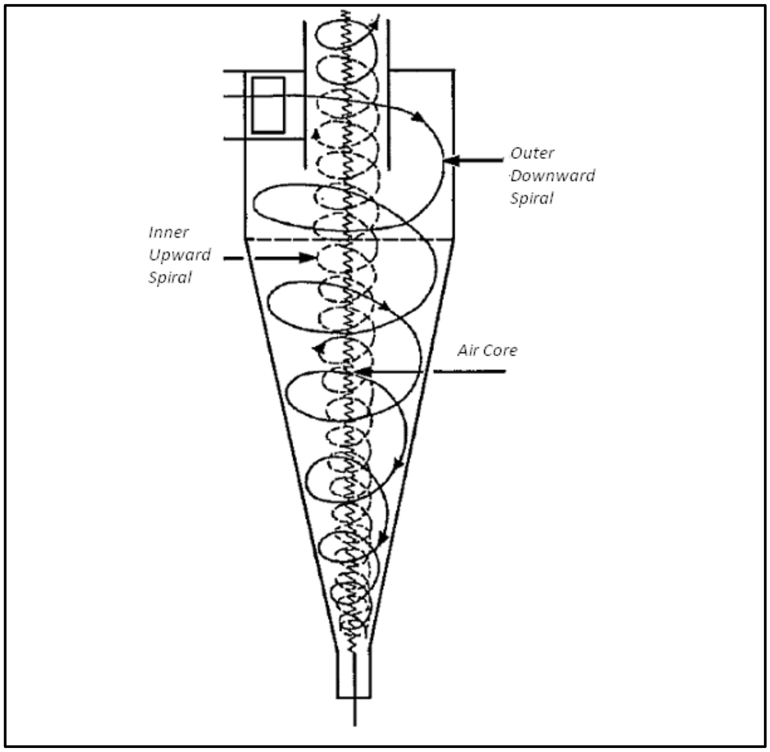

Figure 16: DMC Flow Patterns (Du Plessis, 2009)

The DMC fluid and particle dynamics ensure complex separation phenomena within the cyclone. The multiphase system along with forces acting upon particles and the turbulent flow regime in the cyclone adds to the complexity. Computational fluid dynamics (CFD) are used to study and simulate the behaviour of the complex flow system in a DMC (Narasimha, Brennan, Holtham, Napier-Munn, 2006).

To explain the process of separating coal particles in a dense medium while applying centripetal forces, the fundamentals of particle behaviour in a fluid is discussed. A single particle system refers to a single particle in a fluid. A force is defined as the product of a mass and the acceleration of the mass. Several forces act on a particle moving relative to a fluid. For a spherical particle, these forces include external forces, such as gravity or centrifugal forces,

$$F_E = \frac{\pi d^3}{6} \rho_p a_p \ ,$$

Equation 3

with d as the diameter of the spherical particle, ρ_p the density of the particle and a_p the acceleration of the particle from this force. For gravitation as the external force, a_p is replaced by g (gravitational acceleration), or centrifugal forces a_p is replaced by U_p^2/r_p (centripetal acceleration). Centripetal acceleration has a greater effect on separation in a DMC than gravity acceleration. The velocity of the particles is higher than with the effect of gravity. The external centripetal force drives the separation in a DMC. A coal particle with a high mass will have greater force acting on it than on a coal particle with a low RD. Thus, low quality coal (higher RD) will settle out more rapidly than the low RD floats (higher quality coal).

Drag pressure (or inertial) force due to pressure gradients in the fluid also add to particle behaviour and is given as,

$$F_P = \pi d \mu U,$$

Equation 4

and shear drag forces due to fluid viscosity as,

$$F_S = 2\pi d \mu U,$$

Equation 5

with U being the relative velocity of the particle. A buoyancy force plays a role on the motion of the single particle. This force (acting in the same direction of the drag forces) is defined as the product of the external force acceleration and the mass of the fluid displaced by the particle (Archimedes' law),

$$F_B = \frac{\pi d^3}{6} \rho_f a_e,$$

Equation 6

where ρ_f is the density of the fluid (Rhodes, 1998). The acceleration force of a single particle in a fluid is described in the following equation,

$$F_A = F_E - F_B - F_S - F_P.$$

Equation 7

These fundamental analytical solutions comply with Stokes' law when the particle is moving slowly through the fluid. In this system, the inertial force does not have dominant influence on the particle's behaviour. However, in a single particle system where the inertial forces do play a more dominant role, these analytical solutions just described do not comply. For example, particle with a high acceleration creates more pressure gradients as fluid move 'out of the way' of the particle. A Reynolds number (Re_p) was defined giving the ratio between the inertial forces and the viscous forces on the particle (Rhodes, 1998). High Re_p ratio describes turbulent flow. The Re_p of particle is defined as,

$$Re_p = \frac{dU\rho_f}{\mu}.$$

Equation 8

A drag coefficient (C_D) gives more information on the drag influence. This property is dependent on the Re_p as well as the inertial flow. Stokes' law applies for Re_p smaller than one (Re_p<1) where,

$$C_D = \frac{24}{Re_p}.$$

Equation 9

For Re_p regime higher than one (Re_p>1), a different relationship between C_D and Re_p follows as determined in experimental analysis.

Numerous factors come into play when analysing the behaviour of a coal particle and coal particles in an operation DMC. As coal particles are not spherical, sphericity needs to come into play in the relationship between Re_p and C_D properties. Furthermore, boundary effects, like for instance a coal particle near a cyclone cone wall, also play a role in the flow dynamics. For a multiple particle system, the influence of other particles on a particle opens up another dimension to the study of fluid dynamics (Rhodes, 1998).

In a study conducted on the multiphase flow in a DMC, Narasimha *et al.* (2006) used several complex CFD models to describe the dynamics of the flow in a DMC. This study is one of a few CFD studies done on coal beneficiation DMCs. The CFD model derived included turbulence models, multiphase modelling, medium rheology, medium with size distribution models and a coal particle-tracking model. With these models, Narasimha *et al*. were able to produce results in agreement to results produced from experiments.

2.3.3.1 CYCLONE CONTROL

High efficiency, relatively low maintenance and large capacity of the DMC enable this unit to generate high yields. Even the slightest change in DMC production efficiency can have a remarkable influence on plant economics (Addison, Jones, Addison, Stanley, Luttrell, & Bratton, 2011). For this reason, control on a DMC system is crucial to keep coal yield and coal quality at an optimal operating point. The control philosophy on the DMC system is described in section 2.3.1.1.

Gupta and Mohanty (2006) did a review on existing optimisation methods in coal beneficiation plants. The equalisation of incremental product quality approach was highlighted as one of the established optimisation approaches. This approach entails the control of the individual beneficiation areas or circuits to achieve the same product qualities as the overall quality target defined for plant product. With this approach, the overall yield of the plant is maximised. This conclusion is used in a study conducted by Addison *et al.* (2011) on the development of a multi-stream monitoring and control system for DMCs. DMCs are usually installed in two or more parallel units to meet production specifications. The yield of clean coal is maximised when the units in parallel operate to achieve the same yield or operate at the same separation RD.

This concept is emphasised using the following example taken from the study conducted by Addison *et al.* (2011). Consider two DMCs operating in parallel, identical and both capable of producing coal quality of 8% ash at a RD of 1.55. In these operating conditions, the overall yield of the two DMCs is 69.6%. The DMCs are also capable of producing the same overall quality coal, however one DMC operates at a RD of 1.59 producing coal with 8.5% ash and the other DMC operates at a RD of 1.51 producing coal with an ash quality of 7.5%. The combined overall ash quality of the two DMC in the second scenario is still 8%, however, the overall yield decreases to 68.2% (a yield decrease of 1.4%). A lower separation RD ensures a lower yield and the loss of good quality coal (e.g. coal with 7.5% to 8% ash quality). With an increase in RD, higher ash quality coal is produced and the second DMC needs to compensate for the high ash percentage in producing lower than quality set point coal. A RD difference of 0.08 is the cause for this reduction in overall yield. Addison *et al.* (2011) calculated a revenue loss of $2.9 million annually due to the separation RD difference between two DMCs in operating in parallel.

The control of a DMC is dependent on the RD separation density. The quality and yield production of coal in DMCs are regulated in adjusting the separation RD as explained in section 2.3.1.1. The control of the DMC's separation RD at Exxaro's open-pit mine, GG, is dependent on an operator adjusting the RD set point for optimum coal yield and quality (Van Zyl, 1998). According to Addison *et al.* (2011), real-time calculation of separation is a vital input into a DMC control system. According to a citation on work done by Wood (1990) the D_{50} cutpoint can be calculated using,

$$D_{50} = D_{50}^{*} + 0.910 E_P \ln\left[\frac{1 - S_U}{S_U}\right].$$

Equation 10

D_{50}^{*} represents the RD cutpoint of an infinitely large particle separated in a medium producing a shear drag force of zero. S_U represents the medium split designated to the DMC underflow, a function of RD of the medium in the underflow, overflow and feed to a DMC. Thus, in calculating the separation RD in real-time the DMC underflow, overflow and feed should be readily available. In most DMC monitoring systems, only the feed to the cyclone banks are monitored. This is the reason for the implementation of a multi-stream monitoring system described in the study conducted by Addison *et al.* (2011).

As mentioned, because of high tonnages the slightest efficiency degrades can have a large impact on the plant profitability. Therefore, it is in the best interest of the plant management to reduce fluctuations in the yield. As confirmed by Meyer & Craig (2010), process control can be used to provide process improvement ensuring the DMC circuit run closer target, ultimately decrease revenue loss due to DMC process deviations.

2.3.4 SPIRAL CLASSIFICATION

Spiral classifiers are simple pieces of equipment responsible for complex separating actions that include centrifugal force, gravity, friction on the spiral surface and the drag of the feed slurry. The separating process in a spiral classifier is based mainly on the gravity differentials between the materials being separated (Perry, 1997). A spiral coal classifier typically consists of six complete turns of spiral shaped channels. Spirals in series ensure more effective separation at lower installation and operational costs relative to other separation units. Figure 17 shows the simplified illustration of a spiral including the different design parameters.

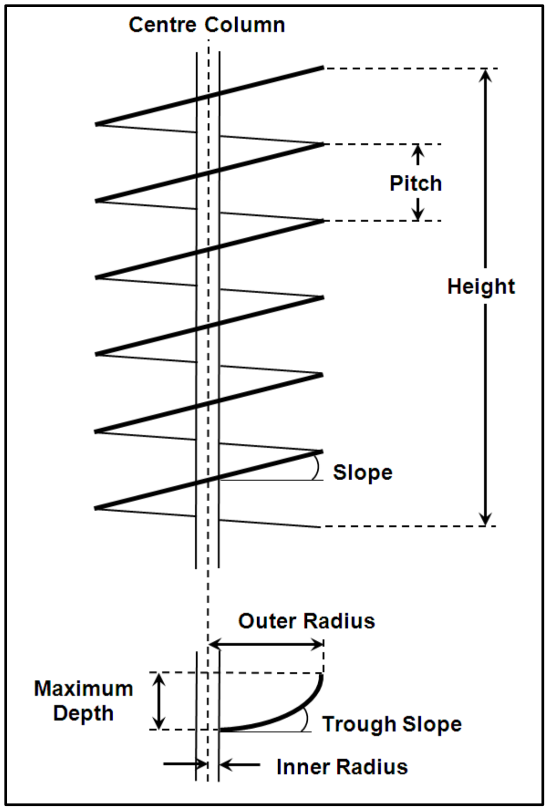

Figure 17: Design parameters for a spiral (Das *et al*., 2007)

The flow regimes produced on an operational spiral insure the complexity of the spiral separation. Primary and secondary flows display laminar to turbulence flow regimes ensuring separation of the coal slurry into different quality flow regions. Primary flow is the flow of the feed slurry down the spiral. The secondary flow is the radial flow across the trough (Das, Godiwalla, Panda, Bhattacharya, Singh, Mehrotra, 2007). Particles with higher density sink to a higher concentrated bottom region radial flow, moving toward the centre column due to dominant gravitational forces. The lower density particles float to the upper fluid layer flow (less concentrated) moving away from the centre column due to the dominant centrifugal forces (Das *et al.*, 2007). The flow dynamics on a spiral is illustrated in figure 18. Classification takes place at the end of the spiral with dividers put in place to direct the different concentrations to the appropriate exit streams. Higher concentrations are achievable by sending the coal stream through a series of spiral classifiers (Perry, 1997).

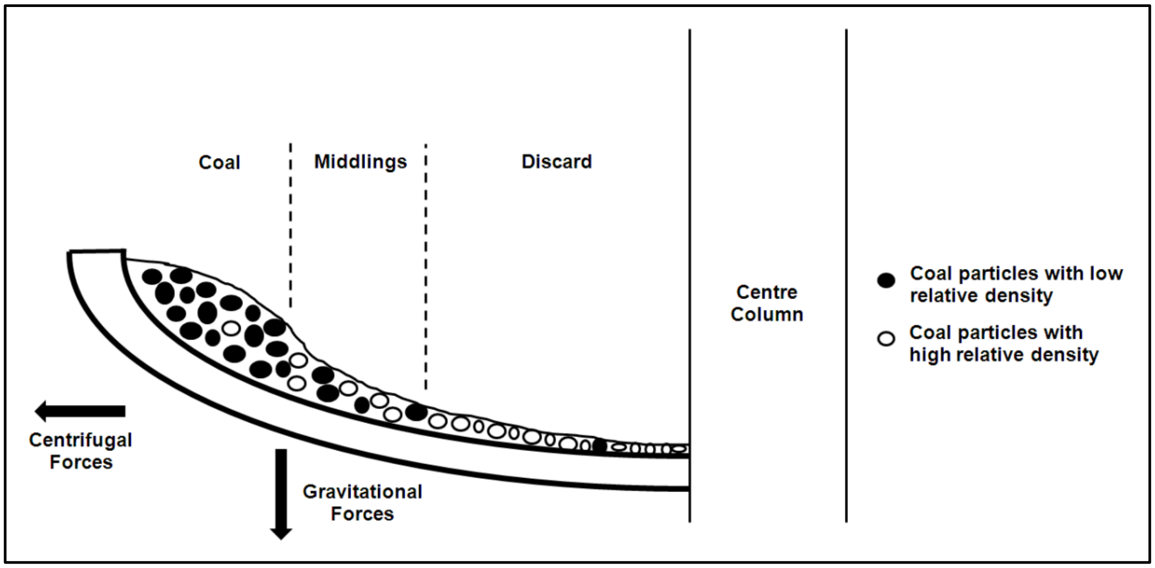

Figure 18: Sectional view of spiral flow pattern (Das *et al*., 2007)

Controlling the concentration of the product in a spiral classifier is not as easy as with DMCs, since the dividers set at the bottom end of the spiral are fixed. The dividers are responsible for splitting the feed into discard, middlings and coal flows after sufficient rounds on the spirals in series. Although the dividers are fixed, a considerable amount of research and analysis are focused on determining the position of dividers to get the optimum separation (Perry, 1997).

2.4 COAL BENEFICIATION AT GG

2.4.1 EXXARO

Exxaro is a JSE listed mining group and the fourth largest coal producer in South Africa with a capacity of 45 million tonnes per annum. This company manages eight coalmines across South Africa (Coal Assets, 2009). For the six months ended 30 June 2010, Exxaro produced 18.3 million tonnes power station coal and 1.2 million tonnes coking coal (Exxaro, 2010). The total coal production for the year 2005 was 42.632

Mtpa[6] with sales divided as follows: Eskom 34.907 Mtpa, other domestic sales 5.579 Mtpa, and exports 1.908 Mtpa (Morgan, 2006).

2.4.2 EXXARO'S WORLD RENOWNED COAL BENEFICATION SITE - GG

The Exxaro open-pit mine, GG, is regarded as the world's largest coal beneficiation complex. Six different plants at GG are responsible for the upgrading of 7 600 tonnes per hour of ROM coal. The open-pit mine uses the conventional truck and shovel operation to produce 18.6 Mtpa of thermal and semi-soft coking coal. This mine had an estimated 740 Mt of coal reserves in 2006 (Exxaro Coal, 2009).

Eighty-two percent of the coal produced at GG is conveyed to Eskom's Matimba Power Station via a 7km conveyor belt. 1.5 Mtpa of metallurgical coal is sold domestically on short-term contracts. Semi-soft coking coals produced at GG are railed directly to ArcelorMittal SA, while approximately 1.1Mtpa of semi-soft coking coal and thermal coal is exported or sold domestically (Exxaro Coal, 2009).

The current infrastructure of the GG mine consists of six coal preparation plants: GG1 to GG6. The GG1 preparation plant comprises conventional beneficiation coal circuits (to be discussed in detail) to produce semi-soft coking coal and power station coal for Matimba power station. GG2 is responsible for the production of thermal coal also using conventional coal preparation circuits, including fine coal beneficiation. GG3 is raw coal crushing facility used for the blending of unwashed coal at Eskom's Matimba Power Station. Metallurgical coal is produced at GG4 and GG5, using beneficiation methods. GG6 comprises a beneficiation facility and is, like GG1, responsible for the production of semi-soft coking coal and thermal coal (Morgan, 2003).

[6]Mtpa: Mega tonnes per annum

Table 3: GG beneficiation plant summary

Beneficiation Plant	Description	Products
GG1	Conventional beneficiation	Semi-soft coking coal, thermal coal
GG2	Conventional fine coal beneficiation	Thermal coal
GG3	ROM coal crushing and blending facility	
GG4	Conventional beneficiation	Metallurgical coal
GG5	Conventional beneficiation	Metallurgical coal
GG6	Conventional beneficiation	Semi-soft coking coal, thermal coal

Exxaro aims to supply a new Eskom power station, Medupi, with 14.6 Mtpa power station coal for the next forty years starting from 2012. The brownfields expansion project at GG will cost an estimated R9.5 billion (Exxaro, 2010).

2.4.3 GG1 PROCESS DESCRIPTION

Different consumers of coal require different degrees of coal preparation, thus no coal preparation plant will be able to comply with all the needs of all the consumers. Coal preparation plants are divided according to levels of coal cleaning achieved. The levels of cleaning indicate the cleaning intensity of the coal. The number of cleaning levels and the intensity of preparation of each level depend on the consumer's quality requirements (Horsfall, 1993). GG1 produces two main product lines: the 10% ash quality semi-soft coking coal product line and the 35% ash power station coal prepared for Eskom's Matimba power station.

A simplified process flow diagram of the GG1 beneficiation plant with its five preparation areas is provided in Appendix A. To start the production of uniform sized coal grades, ROM coal is fed to the crushing and screening section (AREA 01) of the plant. GG1 uses Bradford Breakers to reduce the ROM to an acceptable size range. The smaller particles are sent to the screening section whilst the unbroken waste is sent to a jaw crusher to be crushed and sent to waste dumps. The three streams transporting broken ROM from the Bradford breakers are graded on sieves, the undersize (-18mm) sent to the AREA 02 silos and the oversize (+18mm -150mm) is stored in the AREA 03 silos. The belt scales situated between the sieves and the breakers measure the tonnes per hour coal flow.

AREA 02, AREA 03 and AREA 04 are divided into five beneficiation modules. Each module undergoes the same beneficiation treatment in the respective areas. The belt scales measuring the mass flow of the coals from each silo to the respective beneficiation modules are illustrated in the process flow diagram in Appendix A. Individual module silos are responsible for the storage and feed of the respective modules. The levels of the contents in each of these silos are monitored. The relative densities of the dense medium pumped to the DMC in each module are measured by their own radioactive RD source.

AREA 02 and AREA 03 are regarded as the primary beneficiation areas of GG1. Further grading takes place on sieves when stored coal in the AREA 02 silos is fed to the five modules in the AREA 02 section of the plant. In each of the modules in AREA 02 the undersized coal (-1 mm) is sent to the thickeners, situated in the AREA 05 section for further treatment. The oversize of the sieve is conveyed to the DMCs for beneficiation. The DMCs are responsible for the gravity separation of the coal particles with mixed densities. This treatment focuses on coal cleaning based on the specific gravity quality of the size-reduced coal. The discard of this beneficiation step is destined for the waste dumps while the cleaned coal or floats are stored to the AREA 04 silos.

The AREA 03 silos serve as the coal feeds for the five modules in the Tesca Drum beneficiation area. The coal is graded on sieves and the undersize (-12 mm) is sent to further sieves for degradation. The oversize of the first sieves is sent to a Tesca Drum. The Tesca Drum is a low flow DMS bath. The floats in this beneficiation apparatus are moved and discharged by rotating paddles, while the sinks are lifted from the bottom of the bath by a wheel elevator. The floats discharge to roll crushers for grading after which the coal is sent to the AREA 04 silos. The sinks from the Tesca Drum are destined for the waste dumps.

AREA 04 and AREA 05 serve as the secondary beneficiation for the GG1 preparation plant. At AREA 04 the coal fed from the AREA 04 silos is graded on sieves and the oversize (+1mm -25mm) sent to DMCs for beneficiation and the undersize (-1 mm) is fed to the thickeners in the AREA 05 section. The DMCs in AREA 04 are of main concern for this research project as they serve as the primary control units in the control of the quality of the semi-soft coking coal produced in GG1. The relative densities of the magnetite suspensions of the DMCs (situated in the five modules) are measured by their own radioactive relative density source (RD source). The readings from the RD sources serve as inputs to the SBS, responsible for calculating relative density set points for the module DMCs. The control of the dense medium density is described later. The floats of the DMCs serve as part of the semi-soft coking coal product stacked in the coking coal product stockpile. A belt scale and an on-line ash monitor measures the mass flow as well as the ash content of the coking coal product line, respectively. The sinks of the DMCs together with the coal product from AREA 05 is ultimately stacked on the power station product stockpile.

The -1 mm coal from AREA 02, AREA 03 and AREA 04 is treated in the thickeners at AREA 05. The product of the thickener travels through desliming units and the underflow of these units (-300 micron) is sent to the GG2 preparation plant for fine coal preparation. The -1 mm +300 micron fraction of the coal is treated in the spiral classifier section. Gravity is used to classify or concentrate heavy and light coals in the spirals. This type of beneficiation is not as effective as the DMC processes but is lower in capital cost than other DMS techniques. The coal qualities are stacked either on the coking coal product stockpile, the power station product stockpile or the discard bunker. Table 4 introduces a summary of the product streams and the associated product qualities for each beneficiation area at GG1.

Table 4: GG1 product and product qualities per area

GG1 Areas	Product and product qualities
AREA 1 – Breaking and Screening	i. Waste dump discard; +150 mm unbroken ROM ii. Screening undersize (-18 mm); to AREA 2 silos iii. Screening oversize (+18 mm -150mm); to AREA 3 silos
AREA 2 – Primary DMC Beneficiation	i. Screening undersize (-1mm); to thickeners ii. DMC sinks; to waste dumps iii. DMC floats; to AREA 4 silos
AREA 3 – Tesca Drum Beneficiation	i. Degradation sieve undersize (-1mm); to thickeners ii. Degradation DMC sinks; to waste dumps iii. Tesca drum sinks; to waste dumps iv. Degradation DMC floats and Tesca drum floats; to AREA 4 silos
AREA 4 – Secondary DMC Beneficiation	i. Screening section undersize (-1mm); to thickeners ii. DMC sinks (35% ash); to power station coal stockpile iii. DMC floats (10% ash); to coking coal stockpile
AREA 5 – Spiral Plant	i. Underflow of deslime screen (-300micron); to GG2 beneficiation plant ii. Spiral coal product (10% ash); to coking coal stockpile iii. Spiral middlings product (35% ash); to power station stockpile iv. Spiral discard; to waste dumps

2.4.4 STOCKPILE BUILDING SYSTEM

At numerous instances in the preparation and production of coal, the bulk material needs to be loaded or stored, and stockpiles facilitate this need on a large scale. Stockpiles are used for the storage and at times blending of large tonnages of bulk material. For more consistent product deliverance, blending methods are used to homogenize the quality of the material. Blending is achieved through either the strategic stacking of the stockpile or the reclaiming of the stockpile.

The stacking of a coal product on a stockpile to meet specific quality and economic requirements is a ‘high maintenance’ process. The main purpose of the SBS at GG1 is to fill the complex stockpile management gap. The SBS provides decision support information to the operator and enables the plant to build wet stockpiles with the quality within the required specification without any penalties. The SBS captures real-time data of the on-line ash monitor, moisture monitors and belt scales from LIMS[7] and InSQL[8] databases. Real-time data, delayed laboratory results and the necessary operator inputs such as the target tonnages, target ash, stockpile registration and other inputs that uniquely define each stockpile, are used as inputs for calculations in the SBS (Van Zyl, 1998).

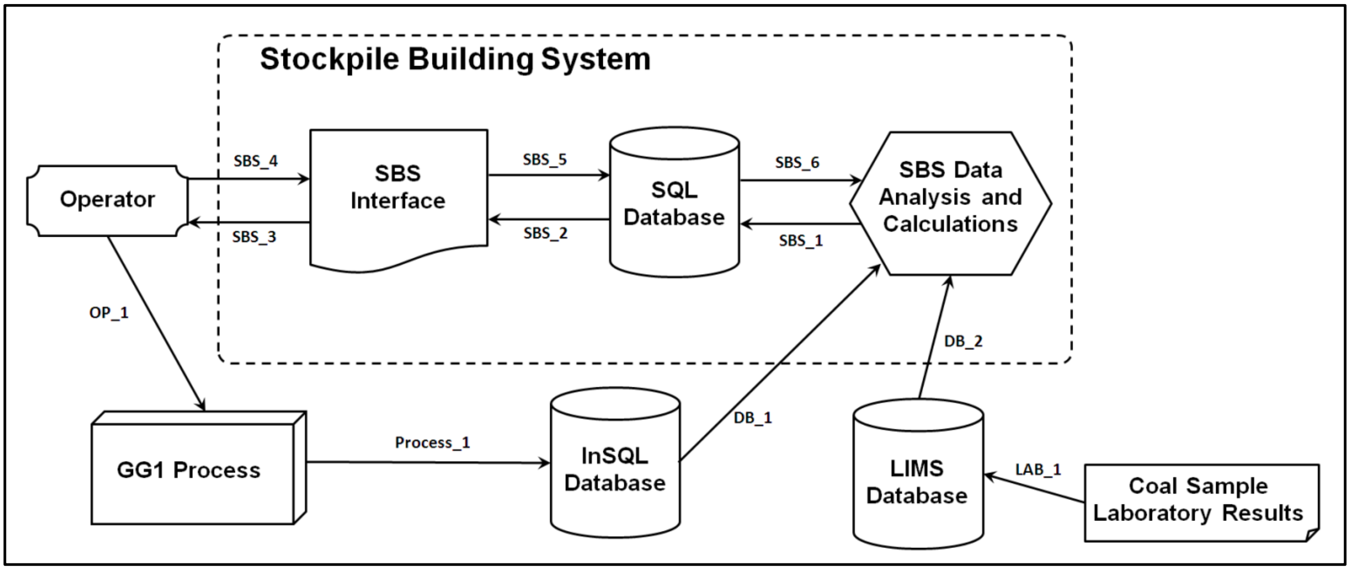

Figure 19: SBS data flow architecture

Figure 19 illustrates a simplified data flow architecture explaining the manual quality control philosophy of the SBS. The data flow as well as data destinations and sources are depicted in this illustration. Table 5 lists the dataflow tags as well as each tag's description.

[7]LIMS: Laboratory Information Management System (database).
[8]InSQL: Industrial Structured Query Language (database).

Table 5: SBS dataflow tags description

Dataflow Tags	Description
Process_1	Data generated from GG1 process sensors are transferred to the InSQL data repository for storage.
DB_1	Data relevant to the SBS are transferredfrom the InSQL database to the SBS system.
DB_2	Results relevant to the SBS from the laboratoryare transferred to the SBS system.
LAB_1	Laboratory results directly introduced to the LIMS repository.
SBS_1	Results from the SBS calculations are introduced into a SQL database containing all SBS relevant data.
SBS_2	All relevant process, laboratory and calculated SBS data are stored in the SQL database.
SBS_3	Results from SBS calculations are displayed on the SBS interface to the operator.
SBS_4	The operator is responsible for a few inputs in the SBS system. The inputs are entered on the SBS interface.
SBS_5	Inputs from the operator are stored in the SQL repository.
SBS_6	Inputs from the operator are used during SBS calculations.
OP_1	Operator uses the information displayed on the SBS interface to make knowledgeable decisions on the input to the process. The inputs to the process are in the form of set-point changes to the five DMC modules.

Sensors placed in strategic locations on the plant generate process values in real-time. The data generated in AREA 04 is sent an InSQL repository for data storage. Spot samples are taken in AREA 04 every hour to monitor the performance of the process. Laboratory techniques are used to analyse the samples taken and the results from the analyses become available after approximately four hours. The laboratory results are stored into a LIMS database. The LIMS, InSQL and operator inputs (via the SBS interface) serve as inputs for real-time SBS calculations. The results generated from the SBS decision support system are stored in a dedicated SQL database. From the

SQL database, the results and necessary information are presented to the operator via a user interface. The operator interprets the information displayed on the SBS interface to make critical set point changes to the DMC controllers in AREA 04. The elimination of the difference between the process variable (overall GG1 coal quality) and the overall coal quality target depends on the operator's experience and knowledge on the process dynamics and controller performance. The operator is responsible for closing the control loop with manual control.

2.4.4.1 SBS PROCESS

The SBS process include the operator's input responsibilities, the real-time calculations, cumulative calculations, hourly processing, shift processing, laboratory information integration, and the completion of the stockpiles.

Operator Input

Several calculations conducted by the SBS depend on user inputs. The operator is responsible for registering new stockpiles during operation. A new stockpile number following a sequential naming convention is needed to identify the stockpile and associate the properties of the stockpile. The operator is also responsible for defining the target characteristics of each stockpile. These characteristics include the target tonnage of the stockpile as well as the target accumulated ash percentage of the final stockpile.

Real-time processing

The SBS reads real-time data available from the InSQL, and updates the SQL database accordingly. A bias, calculated from the results stored in the LIMS database, is determined in the SBS and integrated with the real time ash calculations. The tonnage measurements are also updated in the SQL database.

Cumulative stockpile calculations

The mass accumulation of each stockpile is calculated and monitored on the SBS user interface. The cumulative ash calculated using a weighted average with mass flow. Target ash content is also determined to assist the operator on controlling the DMC overflow quality. The cumulative laboratory values are also included in the cumulative calculations.

Hourly calculations

Hourly values represent the hourly aggregation of the real time results. With this aggregation of real-time values, the laboratory bias is also integrated into the real-time processing.

Laboratory calculations

For validation and adjustment of the online ash monitor measurements, a bias is calculated from the laboratory results to compensate for inaccurate readings. The bias calculation takes place every our when the latest laboratory results are available. The bias for the next hour is the difference between the average percentage ash from the online ash monitor over an hour window and the latest laboratory result. The following equation illustrates the calculations:

Ash Bias for next hour = % Ash from laboratory results – Weighted Average %Ash over previous hour.

2.5 CONCLUSIONS

Chapter 2 focused on providing extensive background on coal beneficiation, especially coal beneficiation at GG1's AREA04 DMC operations. A summarisation of the key concepts is listed below:

1. The most commonly used primary fuel in the world is coal. Coal is a major and vital source of energy in South Africa. This non-renewable energy source play a crucial role in electricity generation, iron and steel manufacturing, mining industries, metallurgy, synthetics and many more aspects of live. Coal beneficiation is thus a crucial manufacturing process worth investigating potential optimisation opportunities.

2. Coal preparation processes mainly utilises DMS techniques in the beneficiation of coal. DMS techniques rely on density separation, i.e. a coal feed is introduced to a

dense medium with a specific separation density ensuring the separation of good quality coal and discard. DMC separation is the drive horse in the beneficiation of coal and the focus of the investigation conducted in this project. The control performance of DMC separation has seen the likes of numerous investigations and theoretical studies. Efficient control of DMCs on a coal beneficiation plant will ensure higher revenue generation.

3. The Exxaro mining group's open-pit colliery GG is regarded as the world's largest coal beneficiation complex. A detailed process description of GG's GG1 beneficiation plant is included in section 2.4.3. The DMC separation performance is monitored and controlled using a SBS system. Process data from the plant as well as laboratory analysis results and operator knowledge serve as input to the SBS. The output of the SBS displays on a user interface. The results from numerous calculations performed by the SBS are display on the interface and the operator is in charge of using knowledge gained from the SBS and adjusts set points to five DMC banks in AREA 04.

CHAPTER 3
PROCESS OPTIMISATION

3.1 INTRODUCTION

Many characteristics of human activities have been fundamentally altered by the new age of the digital computer (Parasuraman & Riley, 1997). At the same time, growing complexity of, for instance industrial manufacturing processes and competition on global markets impose increasingly greater demands for computational intelligence. These factors influence the way industry such as in the mining and manufacturing sector approaches process automation and optimisation. This study underlines the need and value of an intelligent process optimisation approach on a coking coal quality control system.

A common thread in manufacturing processes exists when considering process control. A process has a desired operational behaviour and a control strategy is responsible for minimising the difference between the desired behaviour and deviation from desired behaviour (Wade, 2004). Optimisation on this control concept would be to find the best possible control strategy to control the process on the desired behaviour (Burke & Kendall, 2005). Figure 20 depicts the overall process control and information system hierarchy as proposed by Wade (2004). For proper process control and information distribution, each level should depend on the other. The higher levels will not function without the lower control levels, and on the other hand the control information not distribute without the higher levels. For this study, all the necessary levels are in place, and the focus will fall on the optimisation level.

In order to increase the efficiency of decision support in a decision support system, knowledge of the process is needed (Adriaans & Zantinge, 1996; Feelders, Daniels, Molsheimer, 2000). This knowledge is available in the form of expert knowledge and knowledge gained from the data. Both forms of knowledge, increases to the accuracy of decision support system. The knowledge discovery methodology is a tool used for gaining knowledge out of large amounts of data. This data knowledge combined with problem environment knowledge (discussed in chapter 2) should generate an accurate process model for use in the optimisation.

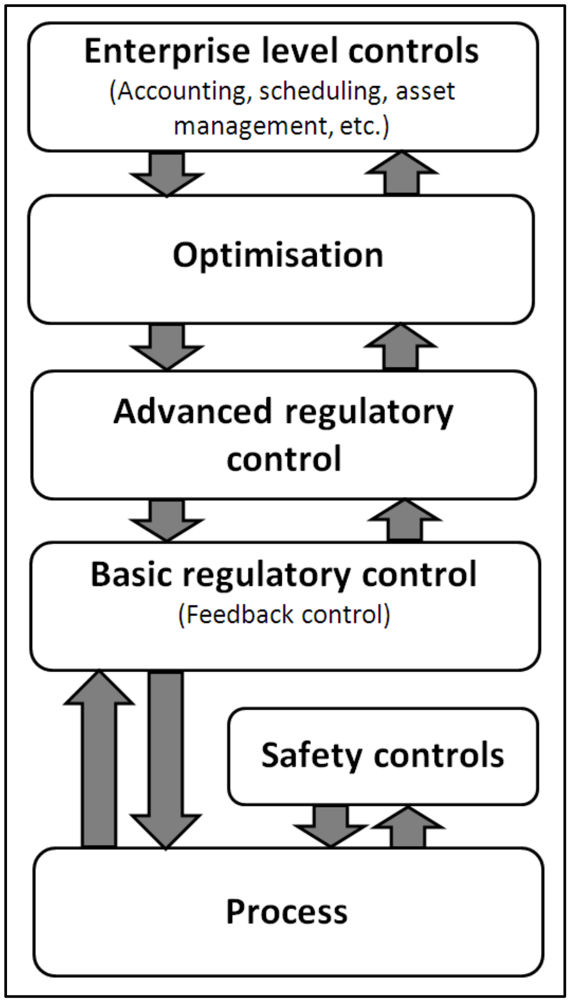

Figure 20: Overall process control and information hierarchy (Wade, 2004)

The purpose of chapter 3 is to provide more background on the optimisation solution approach and development. The role of knowledge discovery in the solution development is discussed in section 3.2. Section 3.3 focuses on process modelling, studies conducted on models generated for coal beneficiation, and neural networks (NNs) as an alternative for process modelling. Genetic algorithms (GA) as an evolutionary algorithm and optimisation component are discussed in section 3.4.

3.2 KNOWLEDGE DISCOVERY

The growing complexity of industrial manufacturing processes and growing rate of the amount of data stored in different repositories are two of the main motivations for effective knowledge extraction processes (Brachman *et al*., 1996). Users' increasing need for more sophisticated information calls for a well-defined and effective process for obtaining this knowledge (Dunham, 2003). Because of this growing demand for a knowledge extraction methodology, the term knowledge discovery appeared in the 1980s. This process is defined as a non-trivial process of identifying valid, useful and understandable patterns in data. Knowledge discovery (KD) is realised as a joint point for different research areas including databases, statistics, mathematics and artificial intelligence[9] (AI) (Mariscal, Marban, Fernandez, 2010). Luo (2008) confirms KD to be very beneficial for the AI research field.

Literature does not have a fixed definition or term for knowledge discovery (Mariscal *et al.*, 2010). Many terms are available for the definition for the process of obtaining knowledge from data. Terms such as knowledge extraction, knowledge discovery from databases (KDD), information discovery, data archaeology and data mining are more than often used. In this literature study, the terms data mining and knowledge discovery will be distinguished in the following definitions:

1. "*Knowledge discovery is the process in finding useful patterns and information in data*." This process includes a data mining step. (Brachman *et al*.., 1996)
2. "*Data mining is the use of algorithms to extract the information and patterns derived by the KD process*." (Dunham, 2003)

The fact that KD is defined as a *process* implicates that this methodology of extracting knowledge involves certain steps. KD steps designations differ from application to application as well as steps designated in literature (Mariscal *et al.*, 2010). Luo (2008)

[9] "*AI mimics human perception, learning and reasoning to solve complex problems*" (Chen, Jakeman, Norton, 2008). Several techniques are available able to conform to the AI criteria such as neural networks, fuzzy models, GAs, and hybrid systems.

defined five definite steps whereas Mariscal *et al.* (2010) defined nine steps to extract knowledge effectively. Although the amount of steps and step names differ, the principals of the steps defined in literature are in alignment. The following KD process procedure, constructed from literature, is chosen for knowledge extraction in this project:

1. Data (Luo, 2008) and task discovery (Feelders *et al.*, 2000): selection of and familiarisation with the data to be analysed and the goals to be achieved with the knowledge discovered.
2. Data pre-processing (Feelders *et al.*, 2000; Luo, 2008; Mariscal *et al.,* 2010) which consists of:
    a. integration of data from multiple data repositories and transformation of data in forms appropriate for mining,
    b. descriptive data summarisation (study of the general characteristics of the data),
    c. data cleaning (removal of data noise and inconsistencies).
3. Data mining: the use of intelligent algorithms for patterns and information extraction.
4. Interpretation and utilisation of the knowledge gained from the KD process (Feelders *et al.*, 2000; Mariscal *et al.*, 2010).

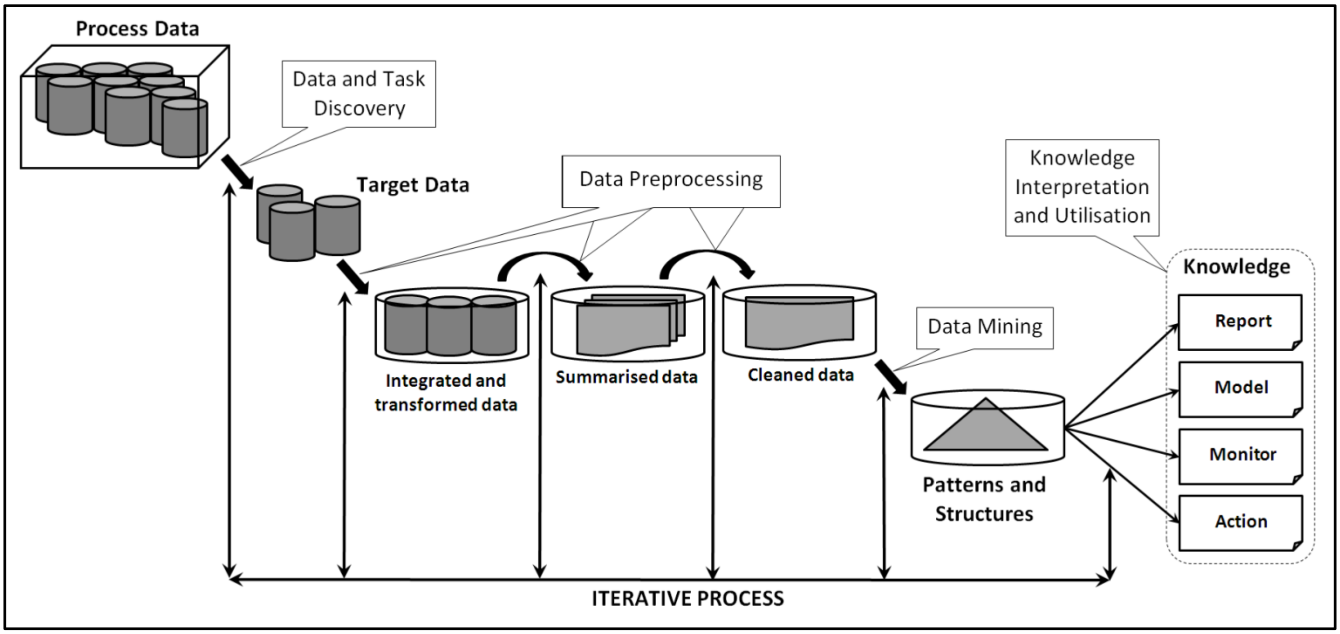

Figure 21: KD process steps (Mariscal *et al*., 2010)

Figure 21 summarises the KD process steps and milestones defined for the investigation. Mariscal *et al.* (2010) includes a "learning the application domain" step, highlighting the importance of prior application or process knowledge. This step is regarded as a required subject area expertise in the KD process (Feelders *et al.,* 2000).

Another important step added by Mariscal *et al*. (2010) is the "using discovered knowledge" step (corresponding to step four of proposed KD process). This step is often neglected as an essential step in the KD process. Actions based on the combination of subject area knowledge and the KD knowledge, should be planned and act upon. Step four of the proposed KD process links to the proposed optimisation solution of this investigation.

Important characteristics of the KD process are the iterative and interactive nature of the process. Many decisions originate at the KD user. This interaction of the user with the KD process determines the iterative degree of the process.

Data warehousing is a crucial component to the effective execution of the KD process. Data warehousing (or data marts) are integrated databases (Feelders *et al.,* 2000) maintaining organisational data from the KD process. This KD component allows for effective data analysis and user access (Luo, 2008).

3.2.1 STEP 1: DATA AND TASK DISCOVERY

The process of becoming familiar with the goals set for the specific task must not be underestimated. This introductory stage of the KD identifies the problem environment characteristics, as well as the data applicable to the problem environment. With adequate subject area expertise the right questions are asked during the KD; useful features could be determine prior to KD initialisation; and interpretation of analysis results could produce pre-emptive courses of action (Feelders *et al.*, 2000)

For the effective extraction of knowledge from data, it is necessary to define the reason for KD. In the production industry, hundreds of thousands of data attributes are available from different data repositories. It is therefore crucial to narrow the data attributes or data tags down to the tags applicable to the matter. In order to accomplish this, it is essential to understand the problem environment and define the goals in solving the task at hand (Adriaans & Zantinge, 1996).

The data could be scattered throughout different relational or operational databases located in different sections inside and outside the problem environment. This makes the identification of the data needed for KD a daunting task (Feelders *et al.*, 2000). Interrelated data sets are stored in database systems and certain software sets are used to access and manage the databases. Relational query languages, such as SQL[10], are used to write database queries, enabling the user to access the data stored in the database. Attributes (data tags), contained in tables retrieved from the database, consist of records of data (Han & Kamber, 2006).

Data and task discovery also include the physical data acquisition. Data acquisition refers to the transfer of the data from the different repositories into an appropriate environment for data analysis, usually the KD data warehouse. With this data

[10]SQL: Structured Query Language.

acquisition, human error and computational constraints can pose a threat to the data integrity (Dasu & Johnson, 2003). This step in the KD process also calls for a clear understanding of the problem environment (Brachman *et al*.., 1996).

3.2.2 STEP 2: DATA PREPROCESSING

Due to the increase in data stored in the industrial manufacturing sector, the data retrieved are more susceptible to noise, inconsistencies and missing data that reduce data quality. Low quality knowledge from data is often the result of ineffective data acquisition. Data pre-processing is the process in which data anomaly elimination takes place as far as possible in order to retain higher data quality (Dunham, 2003).

For effective data pre-processing, the user's knowledge of the problem environment plays an important role. Unforeseen events on a plant such as equipment maintenance schedules or measuring device failures influence the data mining process. The quality of the data transfer and management from a data source to a data management system could also be jeopardised by connection failures. The data pre-processing stage includes three sub-categories in which the data is "cleaned" as much as possible before any modelling takes place.

3.2.2.1 DATA INTEGRATION AND TRANSFORMATION

For effective and rapid KD from data, setting up a working environment for managing the large amount of data, is important. The KD environment consists of a central off-line (or in some cases on-line) data warehouse from where data are managed and manipulated. Instead of browsing through a large number of data tables in different directories, the data warehouse offers the user the chance to search with less effort for the desired data in a central station and extract the data for further data mining (Adriaans & Zantinge, 1996).

Since the data retrieval includes the extraction of data from multiple data sources, proper data integration is needed to ensure accurate data quality within the central KD station. This data integration step is most susceptible to the loss of data quality. Some of the major data integration and transformation challenges include the multiple data sources, time synchronisation, unusual data logs, and dissimilar versions of hardware and software utilised (Dasu & Johnson, 2003).

When integrating different data tables numerous inconsistencies may arise. For example, data table (or database) A was generated logging data in a format dissimilar from the data table B. Entity identification problems occur with the matching of multiple equivalent entities from the different sources. If data table A recorded on an hourly basis and table B recorded when a value became available, these two tables need resampling or transformation in order to synchronize the timestamp without losing the credibility of the data. Data from different hardware and software platforms also pose a problem since, for example, computer access and computer connections can be lost during data management actions. Huge data transformation will be needed to conform to the platform of the data warehouse environment (Dasu & Johnson, 2003). The representation format of the data retrieved from different data repositories through queries may differ. The configuration of the data represented in tables, for example, must be similar throughout the KD process (Han & Kamber, 2006).

Data transformation consolidates all the data into an appropriate data mining framework (or format) for more effective and useful data mining. Smoothing of data noise, data aggregation, data normalisation and data reduction are methods used to transform the data for more effective KD. The data transformation is simply the action taken in order for the data, integrated from other repositories, to retain its accuracy, consistency and significance (Dunham, 2003).

3.2.2.2 DESCRIPTIVE DATA SUMMARISATION

The purpose of this stage in data preparation is to use the statistical techniques available, to identify the typical characteristics of the data. Summarisation is also referred to as generalisation or characterisation as it obtains representative information from the data. Statistical measures are used to determine noise, inconsistencies and other anomalies hidden within the data (Dunham, 2003).

The variability of a dataset is a useful measure in characterizing the different fields within the dataset. The range of a field is a straightforward measure for variability and is highly sensitive to extreme observations. The difference between the maximum value in a field and the minimum value of the same field gives the range of the field (Giudici, 2003).

A more descriptive measure for the dispersion of data relevant to a specific field is the variance of the field distribution. The variance of the different data fields is defined as the degree to which data tend to spread. The asymmetry of a field is also a descriptive tool used to characterise distribution of the fields. If the median[11] of a data distribution is higher or lower than the data mean value (average), the distribution is said to be skew. For a symmetric data distribution, the median should be equal to the average of the distribution (Giudici, 2003).

The classification of observations as outliers is subject to knowledge of the process. The observer needs to confirm the observation as an actual outlier before defining the observation as a definite outlier. Eliminating the data outliers increases the quality of the data and ultimately increases the effectiveness of the KD (Devore & Farnum, 2005).

Graphic displays of the data are also excellent descriptive measures for obtaining knowledge and identifying data anomalies. Display techniques such as scatter plots, time-series trends, histograms and frequency analysis are graphical methods of summarizing the distribution of a specific attribute. These techniques spot outliers and inconsistencies. Scatter plots are effective in determining the degree of correlation between attributes and time-series[12] trends of attributes and histograms are effective in the process of understanding what the data represents (Brachman *et al*.., 1996).

3.2.2.3 DATA CLEANING

After the detection of the inconsistent data identified in the descriptive data summarisation stage, the errors and inconsistencies should be eliminated. In the case of missing data, several methods are available to fill the incomplete data without data integrity. Missing values filled in manually according to the user's judgment, or an

[11]The median is the value which halves the data distribution (Giudici, 2003).
[12]Time-series data are sequential values logged with change in time (Han & Kamber, 2001).

overall constant used to represent the missing values, or the most probable value entered are option available for the handling of missing data. Missing data does not mean erroneous data acquisition, but cases exist where gaps within the data are there for a specific reason. Again, this emphasises the importance of understanding the problem environment relevant to the data (Han & Kamber, 2006).

The removal of noise from the data is called the "cleaning" of the data. Inconsistent data, identified at the descriptive data summarisation stage as outliers, are replaced or deleted according to the judgement of the user. A correlation matrix is a very useful tool in discovering the relationships between the different variables contained in a dataset. Another important data preparation aspect is the estimation of the variable lags, as these time lags play a big role in the accuracy of the time-series modelling.

Time delays, characterised by transportation lag and measurements delays, place rigorous constraints on the performance of a control loop, because the dynamicity of about any industrial process is influenced by process time delays. Thus, eliminating the process time delay could significantly improve the performance and accuracy of the control loop or process model (Hens & Seborg, 1994). A time-delay estimation method such as the cross-correlation based delay analysis is able to evaluate the time delay within a process. During the cross-correlation analysis, the correlation between two variables is calculated: variable A and variable B. The variable containing readings measured prior to the other variable (variable A) is delayed with an appropriate time constant. The next step would be to calculate the correlation of the variable A and variable $B_{t-\tau}$ where τ represents the time constant. The time constant is increased with each iteration until the best correlation is found which will indicate the appropriate delay between the two variables (Mäyrä *et al.,* 2006).

Cross-correlation based delay analysis, described above, estimates a constant time delay between two variables. However, in some processes the delay between two measurements may vary in time. A constant time delay refers to the instance where the effect of a step change on the first measured variable is measured in the second variable after a fixed time delay regardless of the degree of step change or other disturbances. For a time-varying time-delay, the time-delay is not fixed and the time it takes to identify the effect of a step change on the first variable is subjected to disturbances. In this case, time-varying time-delay compensation will improve the accuracy of the system modelling and identification (Tan, 2004).

3.2.3 STEP 3: DATA MINING

As defined previously, in the data mining stage, the user makes use of intelligent algorithms to extract information and patterns from the prepared data. Data mining is the integration of multiple technologies such as data management, statistics, parallel processing and visualisation (Thuraisingham, 1999). Predictive modelling and descriptive modelling are the two data mining task categories (Han & Kamber, 2006). The general properties of the data are characterised during the descriptive model data mining task, while the predictive mining task predicts data values using current data tasks such as classification, regression, time series analysis and prediction fall under the predictive data mining. The nature of clustering, summarisation, and sequence discovery tasks is more descriptive (Dunham, 2003).

In a recent study conducted by Shoa (2010), NNs were evaluated as a reliable data mining technique. This technique introduces high accuracy to date mining, as this technique is able to approximate complex and non-linear process mappings (Motlaghi, 2008). As discussed in previous sections, raw data extracted from process databases are polluted with inconsistencies and poor quality data. The NN has a high tolerance with respect to noisy, missing and incomplete data. Shoa (2010) compared traditional approaches to information processing to the NN approach confirming the value of the NN as a data mining technique.

A detailed discussion on the theory behind NNs is included in section 3.3.

3.2.4 STEP 4: KNOWLEDGE INTERPRETATION AND UTILISATION

The interpretation of the structures and patterns gained from the data mining step is conducted in step 4. From this step, the user may return to previous steps for iteration. With the interpretation stage, redundant or irrelevant patterns may be removed to refine the knowledge gained from the data mining step to a more understandable format (Mariscal *et al.*, 2010). Knowledge on the subject area is necessary to make these decisions (Feelders *et al.*, 2000).

The refined knowledge gained from the KD process can be integrated from simple offline reporting to online decision support systems and knowledge-based systems. Action steps are important in comparing current knowledge of the system with new knowledge gained from the KD process (Mariscal *et al.,* 2010).

3.3 PROCESS MODELLING

In today's manufacturing industries, production plants have in their possession large specialised and integrated data repositories, rich in data capturing the dynamics of the processes. Yet, in numerous facilities the knowledge contained in the databases are not fully harnessed. In addition, the increasing demand in higher quality product at lower cost, keeping to environmental and legislative limits calls for continuous process optimisation. Design and deployment of optimised control systems depend on accurate process models. Empirical models do not always have the capacity to simulate the dynamics of the process accurately due to model assumptions and lack of knowledge of inter-variable relationships (Aldrich, 2002).

Modelling methods are applied in numerous applications in the production industry. These application fields include planning, optimisation and process control (Venkatesan, Kannan, Saravan, 2009). In the field of process control, mathematical or fundamental models are generally used in the controller design phase. This is known as the base case identification of the process (Bauer & Craig, 2008) or the system identification (Wade, 2004). The system identification model should be simple enough for robust control and sophisticated enough as to describe the dynamics of the process accurately, simultaneously (Meyer & Craig, 2010).

Various difficulties arise when it comes to the model generation of manufacturing processes. Difficulties such as process multidimensionality, nonlinear variable relationships, partially understood relationships between variables and lack of reliable data (Venkatesan *et al.,* 2009). Because of the criticality of a process model, it is necessary to overcome such difficulties. The neural network is one option to overcome mentioned difficulties as the characteristics of a properly designed NN can handle these impediments (Venkatesan *et al.,* 2009). This section will focus on the status of coal beneficiation modelling and the application of NN as process model.

3.3.1 COAL BENEFICIATION MODELS

A study conducted by Meyer and Craig (2010) investigates the modelling of a fine coal DMC circuit derived from first principals. A wide range of various models is included in the literature study conducted by Meyer & Craig (2010). From regression models for screens to CFD models on DMCs. Yet it seemed as if none of these models captured the complex dynamics of a DMC circuit completely.

Meyer and Craig (2010) created a novel nonlinear state-space model of a DMS circuit, integrating models from individual units within the circuits. The conservation of overall mass and conservation of mass components were used in the developing of the models from first principals. With numerous valid assumptions and complex techniques, Meyer & Craig (2010) were able to identify and validate the system parameters for a fine DMC circuit. The only model inputs were the feed rate of the ore introduced to the plant as well as the density set point of the dense medium. With the system parameters and model inputs, the model was evaluated using experimental data from an actual fine DMC circuit. The comparison results are summarised in table 6.

Table 6: Simulation comparison results summary (Meyer & Craig, 2010)

Equipment Model	**Correlation**
Magnetite medium water addition	1.00
DMC	
Ash	0.72
Moisture	0.80
Volatile	0.72

The model achieves high accuracy comparing the model output with the actual output. These results from Meyer and Craig (2010) are a benchmark to which any other model could be evaluated.

Addison *et al.* (2011) developed an optimised control system for a DMC circuit. The system includes a multi-stream monitoring system, which monitors the densities of the underflow and overflow of the DMC. Due to most industrial DMC circuits limiting process information to feed medium density, the multi-stream monitoring system was deployed. The feed, overflow and underflow medium densities were used as model parameters. Addison's model is able to predict medium separation RDs in a DMC.

A relative simple model able to capture the complex nonlinear dynamics of a DMC circuit as well as overcoming the lack of reliable data will add great value in the process performance and economic benefits (Meyer & Craig, 2010). The DMC beneficiation process in AREA04 at GG1 combines the operation of five DMC modules to deliver one coking coal product line. Limited information is available from AREA04, regarding the performances of the DMCs. No information is available on the underflows and overflows of the DMCs. In addition, very little information was gathered on the DMC specifications. Thus, an investigation in the AI technique, the NN, as the process is conducted in this study to compensate for the missing information.

3.3.2 NEURAL NETWORK

As mentioned in section 3.2, AI imitates the human's ability to reason and learn to solve complex problems. One of the techniques able to mimic this intelligence is the neural network (also called the artificial neural network) (Chen *et al.,* 2008). The development of the NN was inspired by the biological neural mechanisms of the human brain (Aldrich, 2002). A set of elementary units called neurons or nodes, serves as autonomous computational units of the NN. Each of these units interconnects through weighted connections. Through the combined behaviour of the computational units, the weighted connections and learning algorithms to adjust the weights, the powerful ability of the NN to form generalised representations of complex relationships and data structures in datasets, can be realised (Giudici, 2003).

As illustrated in figure 22 the computational units are organised in different layers: input layer, hidden layers, and output layer. Each node receives input signals from nodes in preceding layers that render the activation of the specific node. The nodes in the input layer are responsible only for the transmitting of the data from the external environment to the NN. Hidden layers are intermediate layers of computational units embedded with activation functions to calculate the output signals, and are not in contact with the external environment. Nodes in the output layer correspond to response variables as the NN results. These results are transmitted to the external environment (Giudici, 2003).

One of the more common types of NN is a feedforward NN using a supervised back-propagation training algorithm. The feedforward attribute of the NN refers to the network architecture. The network is totally interconnected and distinction is made between the different layers. Direction of input flow is only from the input to the output (Taylor, 1995).

Three main classes of learning are the supervised learning, reinforced learning and unsupervised learning. The NN discussed in this literature study uses a supervised back-propagation learning algorithm. In supervised learning of a NN, a desired output target is provided for the network. In other words, the model output is constantly compared to the supervisory output values. The error data generated at the output layer is “back-propagated” to the preceding neuron layers, in order for the weights to update accordingly. The objective of the training of the network is adjusting the weights to an optimum, consequently minimising the error value using an appropriate optimisation algorithm (Taylor, 1995).

3.3.2.1 NEURAL NETWORK ARCHITECTURE

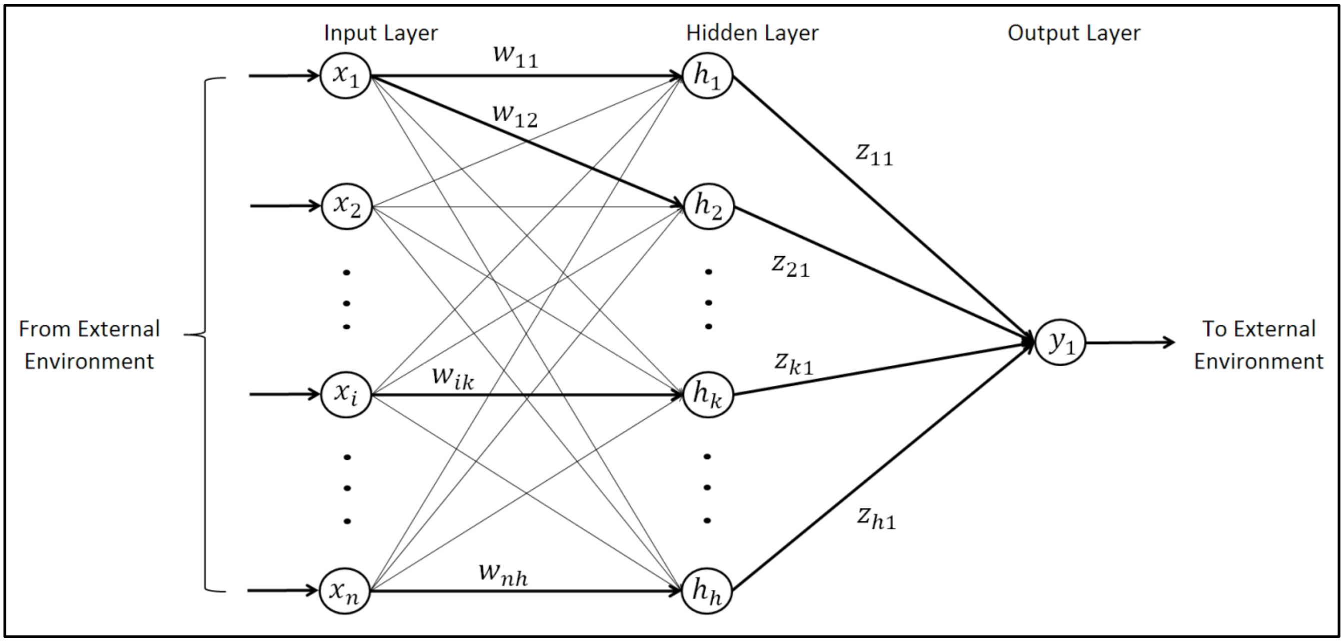

Figure 22: Multilayer Feed-Forward NN (Han & Kamber, 2006)

Figure 22 is a diagram of the architecture (or topography) of a two layer feedforward NN with a single output node. A set of input units $\boldsymbol{x} = [x_1, \ldots, x_n]$ with n neurons is defined as the input layer. The hidden layer consists of h neurodes ($\boldsymbol{h} = [h_1, \ldots, h_h]$) and output layer consists of one output computational unit y_1. Information is sent from the external environment through the input layer via the weighted connections w_{ik} ($i = 1, \ldots, n$; $k = 1, \ldots, h$) to the nodes in the hidden layer. (Giudici, 2003) gives the activation function in the computational units within the hidden layer:

$$h_k = f(\boldsymbol{x}, \boldsymbol{w}_k) = f\left(\sum_i x_i w_{ik}\right) .$$

Equation 11

The activation function is in some cases referred to as the potential of the node (Aldrich, 2002). Figure 23 depicts the profiles of two types of activation functions used in a neuron (Chen *et al.,* 2008).

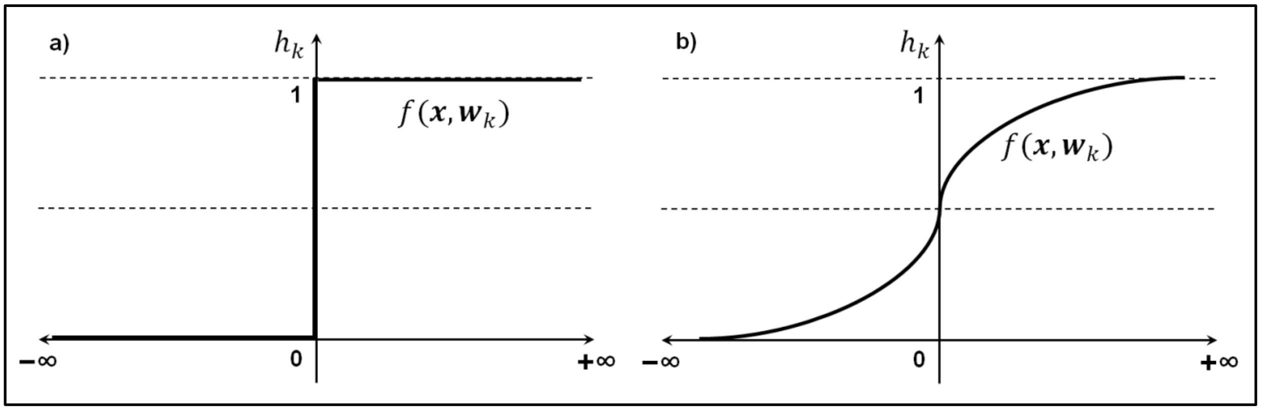

Figure 23: a) Step activation function and b) Sigmoid activation function (Chen *et al*. 2008)

An additional input, called the bias, can be defined as x_0 with its associated w_0 weight. The bias has a fixed value of -1 offsetting the output of the NN to form accurate representation of the process. The weight of the bias is adaptable (Aldrich, 2002).

The neurons in the hidden layer transmit output signals to the output neuron in the output layer. These signals are weighted by the connections z_{kj} (k = 1, . . ,h; j = 1, . . . ,p)between these two layers. The computational unit y_1 produces the final model response variable rendered by the following activation function (Giudici, 2003):

$$y_1 = g(\boldsymbol{h}, \boldsymbol{z_1}) = g\left(\sum_k h_k z_{k1}\right) \quad .$$

Equation 12

Equation 11 and equation 12 are activation functions defined on a set of activation values, which is the scalar product of the weight and input vectors of the node. The activation function may take on multiple forms such as sigmodial functions, or unipolar sigmodial functions depending on the network requirements. Ultimately, the output of the only neuron in the output layer may be defined as (Giudici, 2003):

$$y_1 = g\left(\sum_k h_k z_{k1}\right) = g\left(\sum_k z_{k1} f\left(\sum_i x_i w_{ik}\right)\right) \quad .$$

Equation 13

3.3.2.2 NEURAL NETWORK TRAINING

In order for the NN to produce the desired output given certain inputs, the connection weights require the optimal weighted values. The process of discovering these optimal weights is called the learning or training process of the network. During the training of the network, a dataset acceptably representative of the systems behaviour (called the training set), is introduced into the network via the input layer (Bossley *et al.*, 1995). The importance of the representative nature of the dataset used for training cannot be stressed more than the study conducted by Coit, Jackson and Smith (1998). To assure confidence in the NN, data that adequately and accurately reflects the dynamics and operation range of the process should be used for model generation and validation. A trade-off comes onto play when deciding on the size of the dataset used for training the NN. Too much data used for training can become time-consuming. On the other hand, to little data will defect the model performance on uncommon data interactions. With a smaller dataset, the model also runs the risk of overfitting the data (Coit *et al.,* 1998). Figure 24 illustrates model overfit and model generalisation, where the solid circles represent training data and the empty circles the test data (Aldrich, 2002).

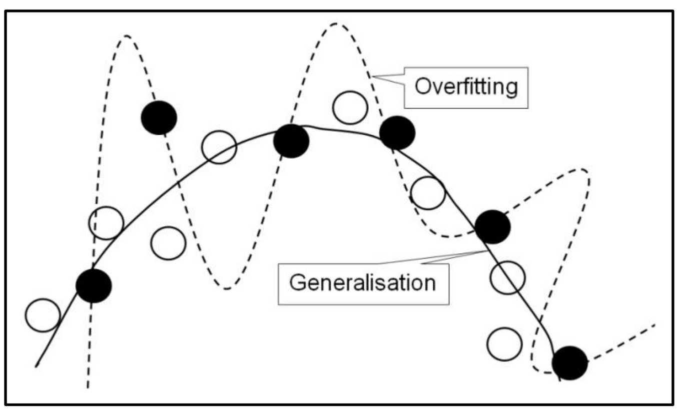

Figure 24: Model overfit vs. model generalisation (Aldrich, 2002).

The goal of the training set is not to reproduce the exact similar results than the original dataset, but to generate a model able to generalise[13] or accurately predict future events

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[13] Generalisation implies that the neural network can interpolate sensibly at points not contained in its training set.

if new data is introduced to the network (Giudici, 2003). A second validation or test set extracted from the main dataset is introduced to the NN after training. This set is responsible to validate the training of the trained model. The learning procedure is terminated as soon as the NN capture the ability to generalise the underlying relationships contained in the data (Aldrich, 2002).

The objective of the training is to relate the output y to a set of functions of $y = f(\boldsymbol{X})$ where $\boldsymbol{X}$ is the input matrix (Aldrich, 2002),

$$\boldsymbol{X} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,h} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,h} \end{bmatrix} \in \Re^{n \times h} .$$

Equation 14

The NN has the advantage of not needing any prior assumptions regarding functional relationships between the input space and the NN output. Supervised NN training is considered for as part of the scope of this project. This training methodology considers the training of the performance of one neuron at a time, illustrated in figure 25. The adjustment of the weights is given as:

$$\Delta w_i = \beta [d_i - \mathrm{sgn}(\boldsymbol{w}_i^T \boldsymbol{x})] \boldsymbol{x} ,$$

Equation 15

where β determines the learning rate. The learning procedure is terminated as soon as the NN capture the ability to generalise the underlying relationships contained in the data (Aldrich, 2002).

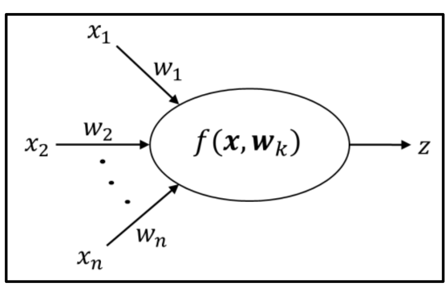

Figure 25: Model of a single neuron (Aldrich, 2002).

The accuracy of the NN after training needs to be evaluated. The model fit, as well as the model generalisation ability defines the model accuracy or efficiency. A quantitative statistical estimator, R^2, describes the model fit. R^2, or the coefficient of determination (as defined by Devore & Farnum, 2005), is the proportion of variation of the measured records explained by the nonlinear model, given by:

$$R^2 = 1 - \frac{\text{Residual sum of squares}}{\text{Total sum of squares}} \quad .$$

Equation 16

A residual is the vertical deviation of a modelled point from the measured point at a given timestamp. The residual sum of squares explains the amount of variation in the measured set not explained by the nonlinear model. The residual sum of squares is defined as follows (Devore & Farnum, 2005):

$$\text{Residual sum of squares} = \sum (y_i - \hat{y}_i)^2 \quad ,$$

Equation 17

with y_i a measured record and $\hat{y}_i$ the modelled value of record i. The total sum of squares is the measure of the total variation from the mean of the measured variable. A larger total sum of squares indicates a larger variability in the measured variable values. This estimator is given by Devore & Farnum (2005):

$$\text{Total sum of squares} = \sum (y_i - \bar{y})^2 \quad ,$$

Equation 18

where $\bar{y}$ is the sample mean of the output space.

The closer R^2 is to one, the more accurate the model describes the variability of the monitored variable. In order to acquire a more comprehensive view on the performance of trained NN, evaluation of the generalisation ability of the nonlinear model is important. The model fit estimated on the training set compared to the model fit of the validation dataset gives an indication of the generalisation capabilities of the trained model. A large difference indicates a poor generalisation of the model, whereas a smaller difference (preferably smaller than 5%) represents a good model generalisation (Devore & Farnum, 2005).

The performance of the training of the NN is evaluated in cross-referencing the training data set with a validation data set also consisting of adequate data to represent the system's behaviour (Giudici, 2003).

The versatility of the NN enables the prediction of continuous data, as well as classification of discrete data. This multi-variable modelling technique is popular due to its ability to detect variable interactions in a complex domain. The NN is not as susceptible to data noise and missing data as other modelling techniques, but the accuracy of the NN prediction is susceptible to the number of inputs. This stresses the importance of the reduction of the dimensionality of the NN input space (Berry & Linoff, 1997). The NN accommodates multiple nonlinear variables with unknown inter-relationships (Coit *et al.* 1998).

3.4 GENETIC ALGORITHMS

3.4.1 GENETIC ALGORITHM DESCRIPTION

The genetic algorithm (GA) is a stochastic, parallel, global search method (Venkatesan *et al.,* 2009), categorised under the evolutionary algorithms group along with evolution strategies and evolutionary programming. The motivation behind the design of the algorithm was to model the biological processes of natural selection and population genetics (Fleming & Purshouse, 2002; Goldberg, Sastry, Kendall, 2005). This optimisation methodology is robust in its search functions, able to locate global optima in large and complex spaces (Venkatesan *et al.,* 2009).

The GA is based on several biological evolution features (Venkatesan *et al.,* 2009). The algorithm searches for the best solution in a population of possible solutions with an individual representing a particular possible solution to the problem. Individuals in the population (also referred to as chromosomes) are generally expressed in genetic code (Goldberg *et al.,* 2005). The population is evolved over generations and good solutions are distinguished from bad solutions in each generation. The evolution of the population over generations produce better solutions (individuals) to the problem until the best solution is identified (Fleming & Purshouse, 2002).

A fitness function is responsible for distinguishing between good and bad individuals. The fitness function could be an objective function derived from a mathematical model, or a subjective function allowing humans to identify the better solutions (Goldberg *et al.,* 2005). The fitness function determines how good the individual solves the problem. A fitness value is assigned to each individual in the population. The higher the fitness value the better the individual is at solving the problem (Fleming & Purshouse, 2002).

The population property of the GA is user-defined. This property affects the scalability and performance of the GA. A too large population will result in the utilisation of unnecessary computational time (Goldberg, 2005). The GA is a computation intensive algorithm. This is the main reason for GA being infeasible for online control applications (Fleming & Purshouse, 2002). One of the objectives for the design of a GA would be to decrease the time until computation termination as far as possible. On the other hand, a small population could lead to premature convergence resulting in the algorithm not finding the global optima (Goldberg *et al.*, 2005).

As soon as the population size has been set, the problem encoded in a chromosomal manner and the fitness function identified, the iteration of the evolution process can be initiated. Fleming and Purshouse (2002) proposed a schematic representation, depicted in figure 26, of the progress of the GA. Many modifications to the parameters of a GA have been investigated to adapt the specific problems. Fleming and Purshouse (2002) recommend using the GA search computing as a general problem-solving procedure and adapt the GA parameters to the specific problem.

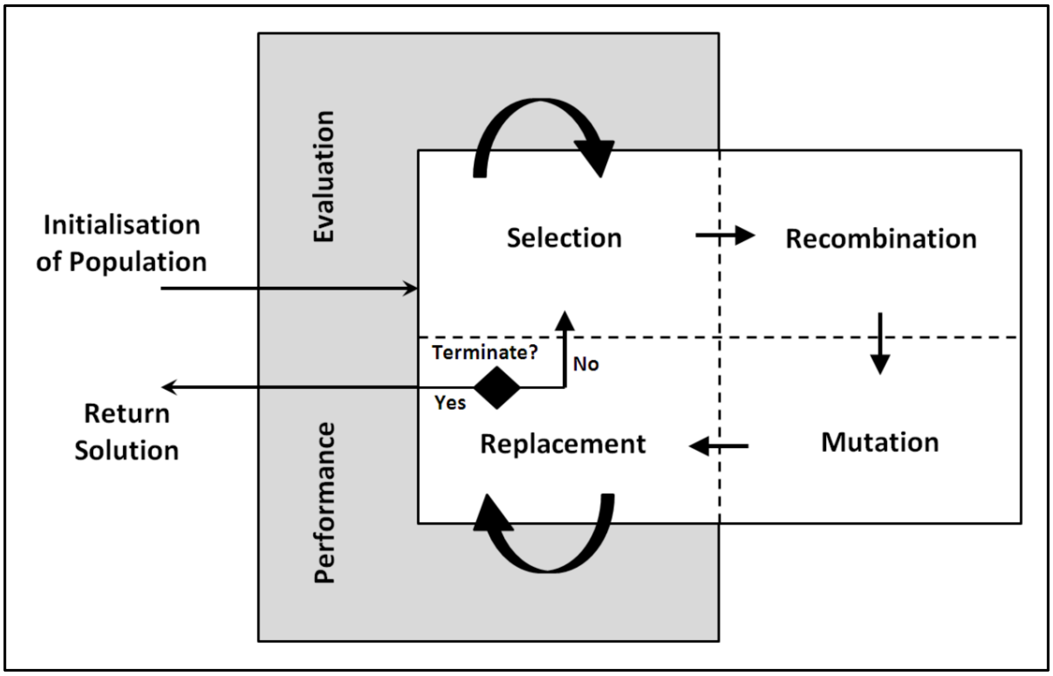

Figure 26: Schematic representation of a GA (Fleming & Purshouse, 2002).

1. Initialisation of population

As mentioned, the population of the search space is a user-defined GA parameter. The individuals are selected at random; however, expert knowledge on the search space can be incorporated for more effective optimum solutions search (Goldberg *et al.,* 2005). The initialisation of the population entails the introduction of the selected population to the iteration stages of the GA. Various population topologies have been investigated. An example of a variation in the population approach is the implementation of island populations. The island populations search for the optimal solution in parallel (Fleming & Purshouse, 2002).

2. Evaluation

The evaluation stage evaluates the fitness of each individual in the initialised population or the offspring population based on the fitness function (Goldberg *et al.,* 2005).

3. Selection

The selection operator is also a user-defined parameter which either introduced the initialisation population to the following stages of the GA or the selection is done on the next evolved generation. The main objective of the selection is to impose a survival-of-the-fittest strategy where only the fittest individuals are selected for the next evolution (Goldberg *et al.,* 2005). After sufficient amount of generations or as soon as the population converges to a global optima, the selection process stops and the GA process is terminated.

Two classes of selection are classified in the selection stage. The proportionate fitness selection relates a selection degree per individual proportional to the fitness of the specific individual. The roulette-wheel and stochastic universal selection strategies are part of the selection class. The ordinal selection class includes strategies such as tournament selection and truncation selection. During a tournament selection *n* amount individuals are entered into a tournament and the fittest individual are selected as the parent. This selection then requires *k* tournaments to select *k* amount of parent individuals (Goldberg *et al.,* 2005).

GAs are able to search for the global optima while satisfying hard constraints[14] as well as soft constraints[15]. The fitness function is responsible for directing the search algorithm to adhere to the constraints as far as possible (Onnen, Babusika, Kaymak, Sousa, Verbruggen, Isermann, 1997).

4. Recombination

The recombination (or crossover) parameter is responsible for the creation of new and possible better offspring from the selected parent individuals, keeping some parental traits with each offspring. Many crossover methods have been adapted for specific performance on the creation of the offspring (Goldberg *et al.,* 2005). The recombination operator has a user-defined crossover probability. With the selectable crossover

[14]Hard constraint: the constraint defined in particular problems that have to be satisfied. If not satisfied, the solution will lead to an infeasible result (Burke & Kendall, 2005).
[15]Soft constraint: Unlike a hard constraint, it's not essential to satisfy a soft constraint. Multiple soft constraints in a problem could lead to the tradeoff situation where one constraint is satisfied in more than the other (Burke & Kendall, 2005).

schema and user-defined crossover probability, the potential of a GA to perform in a manner suitable to the specific problem is realisable.

Figure 27 illustrates three recombination methods. The three-point crossover is grouped under the *k*-point crossover. Two encoded parental individuals are recombined at three (or k) places as indicated. The newly created individuals are called the offspring from the parents (Goldberg *et al.,* 2005). The offspring individuals increase the individual search area.

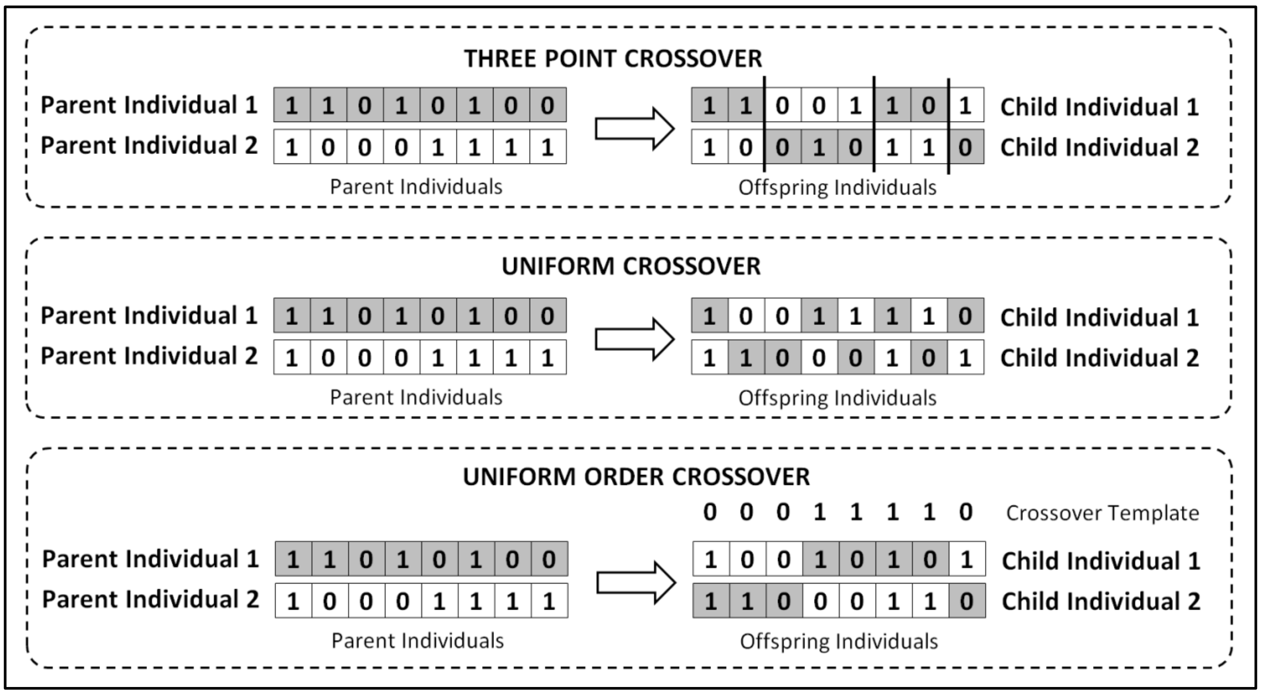

Figure 27: GA recombination methods (Goldberg *et al*., 2005)

The uniform crossover method uses a second parameter to identify probability of the crossover called the swapping probability. An additional parameter adds to the complexity of the evolution stages and thus to the calculation intensity. On the other hand, the uniform crossover could enhance the search for global optima during optimisation (Goldberg *et al.,* 2005).

The uniform order crossover method makes use of a template-encoded individual responsible for selecting the points of crossover. With this crossover method, the user is able to lay more focus on certain components of the solutions individuals. Expert knowledge on the system optimised will give more certainty on the structure of such a template (Goldberg *et al.,* 2005).

5. Mutation

The crossover operator is effective in increasing the search area of the GA and thus increases the fitness of the population effectively. However, because recombination includes the altering of two or more parents the chances of offspring keeping the traits of their parents exist. The mutation operator is responsible for the manipulation of a single individual's traits. In this way, the chance of a less fit individual to retain its place in the population is decreased. Common practise introduce a lower probability than the recombination operator does. The bit-flip mutation methodology is the most common of the mutation methods. Like all the user-defined GA parameters, the mutation operator has numerous variations (Goldberg *et al.,* 2005).

6. Replacement

After the population selection, recombination of the parental individuals to produce offspring and mutation of individuals, the newly created offspring population need to replace the parental population. Several replacement techniques are available. With the replacement of parental individuals with offspring, the objective of the GA should not be forgotten: the average fitness of selected populations should increase with evolution to converge to optima (Goldberg *et al.,* 2005).

The most common techniques include the delete-all, steady state, and elitism replacement techniques. The delete-all technique replaces the full parental population with the newly created offspring population. This technique is less computational intensive as it is parameter free. The steady-state method makes use of a parameter to select *n* individuals and replace them with newly created individuals (Goldberg *et al.,* 2005). The elitism technique ensures a portion of the fittest individuals from the parent population stays in the new population (Fleming & Purshouse, 2002).

7. Iteration and termination

Steps 2 to 6 are repeated depending on the criteria of the termination function. This function is user-defined and determines the amount of generations before termination, or the iterations will terminate if the search found an optima (Goldberg *et al.,* 2005).

3.4.2 GENETIC ALGORITHMS APPLICATIONS

As mentioned, GA is a robust search and optimisation methodology able to use incremental search mechanisms to find the global optima in complex problem environments (Fleming & Purshouse, 2002). GAs are in many ways more competent in finding the global optima for nonlinear problems than traditional search methods (Onnen *et al.*, 1997).

Numerous literature studies are available on the GA's contribution to process control. Fleming and Purshouse (2002), Renders, Nordvik and Bersini (1992) and Kristinsson (1992) contributed to the understanding of GAs' performance in process control systems. The GA's ability to exhibit properties such as discontinuity, time-variance, randomness, and noise handling empower the GA to search optimal solutions for highly complex control systems. However, the GA is not suitable for problems where the solution is almost linear. For these problems, techniques that have a more conservative approach are able to produce results that are more competitive (Fleming & Purshouse, 2002). Another downside of the GA is the infeasibility in an online control system. This is due to the computation intensity required by the GA to produce results. Online control systems are often mission-critical and safety-critical applications, which requires effective and real time solution outputs (Renders *et al.,* 1992).

Renders *et al*. (1992) conducted a literature survey discussing different process control applications for GAs. Two groups were identified, off-line control applications and on-line control applications. For off-line control applications, GA is said to be a powerful tool in estimating optimal set points of process units or realising efficient strategies for complex problem environments. A representative process model will enable numerous GA trails for optimisation off-line without endangering the efficiency of online systems.

Renders *et al.,* (1992) also explains that the GA can offer accurate results in the system with very slow dynamics. An online GA application for process control must comply with certain circumstances for the GA to produce useful results. This list of circumstances includes an accurate process model as well as a large time interval between control samples. Venkatesan *et al*. (2009) implemented the integrated platform of representative process model (artificial neural network) and GA as optimisation tool (discussed in Renders *et al.* (1992)) in the optimisation of machining processes.

Mohanty, Gupta, Mahajan and Biswal (2007) investigated a multi-objective GA application to maximise the revenue generated by a coal beneficiation plant. A study conducted on the GA's involvement with the coal manufacturing industry showed that the GA is familiar to this industry. Several studies were done on single unit optimisation as well as plant wide optimisation applications. However, from this paper no study seems to be available on DMC set point optimisation using GAs as conducted in this project.

3.5 CONCLUSIONS

This investigation focuses on extracting the necessary information from the data in order to simulate dense medium cyclone (DMC) process behaviour and applying the extracted data knowledge to the optimisation of the quality control at GG1. Chapter 2 discussed the background of the problem environment for this investigation. Chapter 3 provided background on an approach for the optimisation of the process described in chapter 2. The list below provides a summarisation of the crucial concepts derived from this chapter.

1. Apart from the knowledge gained from the process in chapter 2, knowledge enclosed within the vast amounts of data attributes at GG1 need to be extracted and combined with the process knowledge. It is for this reason that the KD process was investigated in chapter 3. This process uses different iterative steps in order to extract underlying data relationships and patterns from the process data. The progress of this investigation is guided using the process methodology the KD process offers.

2. Design and deployment of optimised and control systems depend on accurate process models. Empirical models do not always have the capacity to simulate the dynamics of the process accurately due to model assumptions and lack of knowledge of inter-variable relationships. It is for this reason the NN, a multi-variable modelling technique, is investigated as a possible DMC process model. The NN is a popular modelling technique due to its ability to detect variable interactions in a complex domain and accommodate data noise in the model. The NN is also a popular data mining technique used to discover patterns in process data.

3. GA is a robust search and optimisation methodology able to use incremental search mechanisms to find the global optima in complex problem environments. GAs are in many ways more competent in finding the global optima for nonlinear problems than traditional search methods. Various literature studies are available focusing on the GA implementation in the manufacturing industry. Among these studies are literature based on the application of GA on coal beneficiation process for process optimisation. GA has the advantage of effectively finding the global optima in a search space. However, the downside of GA implementations is the computation intensive aspect of the GA. GA is mostly discarded for online control systems. Due to this constraint (among others), the SBS optimisation will not be in the form of automation (replacing the responsibilities of the operator with automatic set point implementation) but the optimisation of the set point calculation and decision support the optimised SBS will offer the operator. The details on the development of the optimisation solution for the SBS at GG1 are discussed in detail in the preceding chapters.

CHAPTER 4

DATA AND TASK DISCOVERY

The process of becoming familiar with the goals set for the specific task must not be underestimated as mentioned in chapter 3. This introductory stage of the KD identifies the purpose and objectives of the study, as well as the identification of data relevant to the problem environment.

An investigation in the quality control on a coking coal production line at Exxaro's GG plant, GG1, was initiated in 2009. This investigation discusses the optimisation approach used and the results obtained to identify benefits for an optimised decision support strategy on the production line at GG1. Chapter 4 elaborates on the project purpose, identifying the problem environment and the constraints accompanying the tasks. The optimisation approach and objectives is also included in this chapter.

The data acquisition stage produced numerous data sets scattered over three separate databases. Additionally the challenge of identifying the key data tags arose. This chapter includes an extensive description of the data sets and databases present at GG1, as well as discussion of the different data sources.

4.1 TASK DISCOVERY

From the information gathered from multiple sources, including GG1 metallurgists, engineers and relevant documentation, the main issue identified was the inefficient quality control on the 10.3% ash semi-soft coal product at GG1, leading to some stockpiles not achieving an average ash content of 10.3%. The loss of good quality coal due to fluctuations in the average ash accumulation of the coking coal delivery is also another disadvantage of this inefficient quality control. As described in chapter 2, the SBS is responsible for numerous calculations and visual representation of the calculated results. The SBS gives percentage ash content as an output to the operator and the operator is then responsible for the quality control of the semi-soft coking coal stockpile (10.3% ash average). The operator uses manual control to adjust the separation RD of the magnetite suspension introduced to the DMCs situated in the five modules.

4.1.1 PROBLEM STATEMENT

This section summarises the issues relevant to the problem environment. The issues listed need to be addressed in this investigation to ensure an optimised solution.

1. The output, given by the SBS to the operator, is a calculated ash set point. Every five minutes this set point is updated and the operator adjusts the RD of the correct medium, as explained in chapter 2. This implementation is a constraint since the operator needs to adjust the separation RD from an ash content set point. The performance of the manual control will depend on the knowledge and experience of the operator. If the operator has little experience and knowledge of the system, adjusting the set points of the dense medium RD from an ash percentage value (presented on the SBS user interface) will be inferior to that of an experienced operator.

2. The adjustment on the control element takes place in small increments, as to view the outcome of the adjustment from the on-line ash monitor (situated on the coking coal product line) as an ash percentage. The effect of an adjustment on the RD in the correct medium tank (see figure 11) is visible after an approximate fifteen-minute delay[16], depending on if the RD is increased or decreased (Rautenbach, 2009a). In effect, the operator controls the quality of the stockpile with the adjustment of the RD in the correct medium tank on a trail-and-error method. Again, the more experienced the operator the more efficient the control. This results in a quality control producing a high

[16] Villanueva and Lamba (1998) conducted a study on a knowledge-based operator guidance system for coal washing plants operated by Broken Hill Proprictary Limited (BHP) at Port Kembla, Australia. This operation guidance system consists of several functional components including process models, monitoring and optimisation. The process investigated is a relatively slow process also with an approximately fifteen-minute delay before a control action is noticeable.

variance in the controlled process variable, which leads to a product containing a portion of unwanted power station coal. Ultimately, this control is responsible for a lower quality product and financial loss.

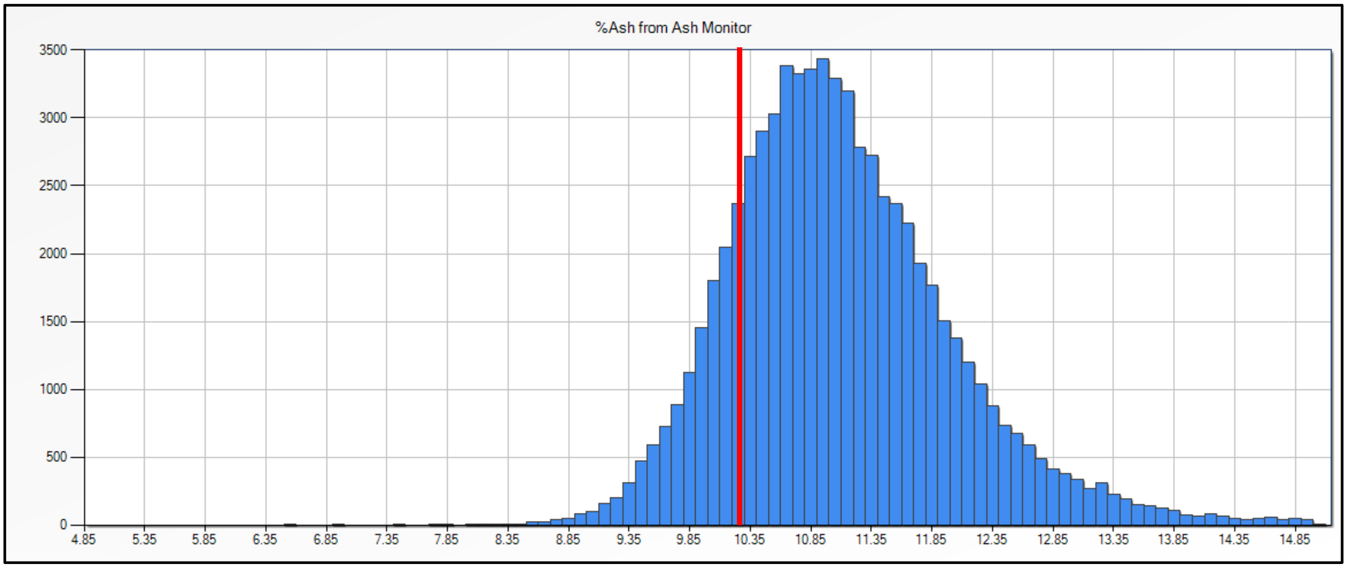

Figure 28: Ash content probability distribution as measured from the ash monitor

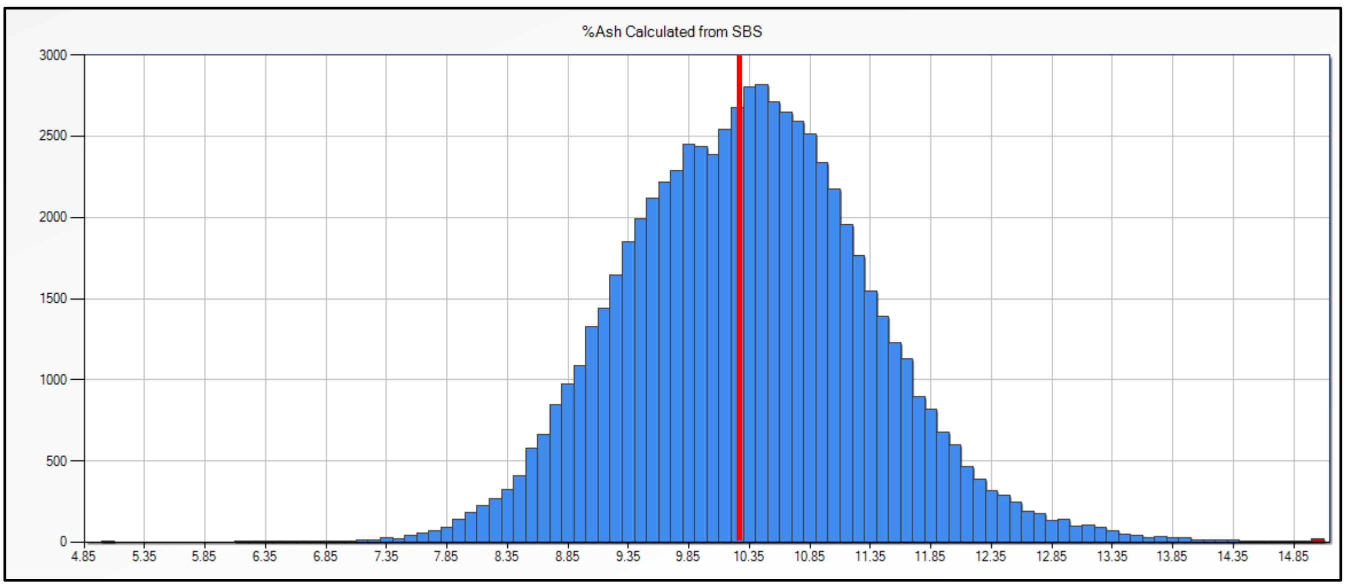

Figure 29: Ash content probability distribution as calculated in the SBS

Figure 28 shows the probability distribution of the ash content as measured by the online ash monitor. The variance of this distribution is 1.40 and evident from this figure the average ash content, 11.37% ash, in the product line deviates from the target of 10.30% ash. The distribution of ash content as calculated in the SBS is depicted in figure 29. The variance is higher at 1.59 than the ash content distribution measured directly from the ash monitor. However, the average is 10.61% ash, significantly closer to the target ash content. This is because the operator controls the ash content on the product line based on the bias-updated ash content. The difference in the two measurements and the effect this difference has on the study is also investigated.

3. The SBS uses the data from the on-line dual gamma ash monitor measuring the ash content on the coking coal product line. This ash monitor is inaccurate (Rautenbach, 2009a) and the readings from the monitor are updated every hour using a calculated bias. The bias updates whenever the new laboratory results (usually with a three to four hour delay) are available. This means that the key process indicator (KPI) is updated with measurements taken three to four hours prior to the current measurement. As discussed in section 2.4.4, the bias is determined on the lab results and the average coal quality over an hour period. If for instance the coal quality deviates from normal operation in the time the spot sample was taken, a negative effect will be seen in the hour the bias was updated by that specific spot sample laboratory results. The operator will not be aware of this and will manually adjust the set points to accommodate for this erroneous bias.

4. For manual quality control inducing variance to the product-line ash quality, the secondary DMCs in AREA04 can produce a coal product with ash content lower than the ash content set point. Thus, the ash content of the coal on the product line is lower than it should be. This means that the sinks in the DMC contain coals with ash content of 10% and ultimately a loss of good quality coal. These coals are sent to Matimba Power Station along with the accompanying metallurgical coal. On the other hand, if the beneficiation DMCs in AREA 04 produce floats with ash content higher than the set point, the poor quality coal ends up on the product stockpile and an increased density is necessary in the DMC in order to compensate for the low quality coal on the stockpile. In addition, the fluctuations result in a decrease in yield as explained in section 2.3. The control of DMCs producing a coal quality with less fluctuation is a supported control strategy as proven from literature in section 2.3.

5. Another factor influencing the control of the coal quality on the stockpile is the fact that the product delivered by the spiral classifiers cannot be controlled or monitored due to no data being logged for this section. This means that the control of the DMC separators needs to compensate for this factor for proper control of the coal quality on the stockpile.

4.1.2 PROJECT OBJECTIVES

The purpose of the research is to investigate the benefits of an optimised manual control[17]on the relative densities of the correct medium in the five modules located in AREA 04. This is done combining the necessary knowledge gained from a KD process and process background studies to simulate the process using an accurate process model and effectively optimise the SBS output to the operator for better quality control. The NN technique will be used to model the process and a GA will be responsible for the optimisation of the set points provided to the operator. Figure 30 illustrates the objective of the optimisation solution investigated. The aim is to decrease the variance in the ash content distribution in the final coal product. In addition, each stockpile stacked should contain predefined average ash content, usually 10.3% ash (Rautenbach, 2009a).

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[17]The automation of the control strategy currently deployed at GG1 was considered during initial analysis. Automation is defined as the replacement of human functions with a computer agent (Parasuraman & Riley, 1997). According to automation study done by Kaber and Endsley (1997), a decision support system integrating human decision-making and computer processing have proved to produce inferior performance. More than that, the system awareness also improves with this integration. The human's flexibility and adaptability to unforeseen process conditions makes this integration of humans and computers processing a more valuable implementation (Parasuraman & Riley, 1997). To prevent expert knowledge loss and system awareness degradation, the responsibilities of the SBS and the operator will stay the same for the optimised solution under investigation.

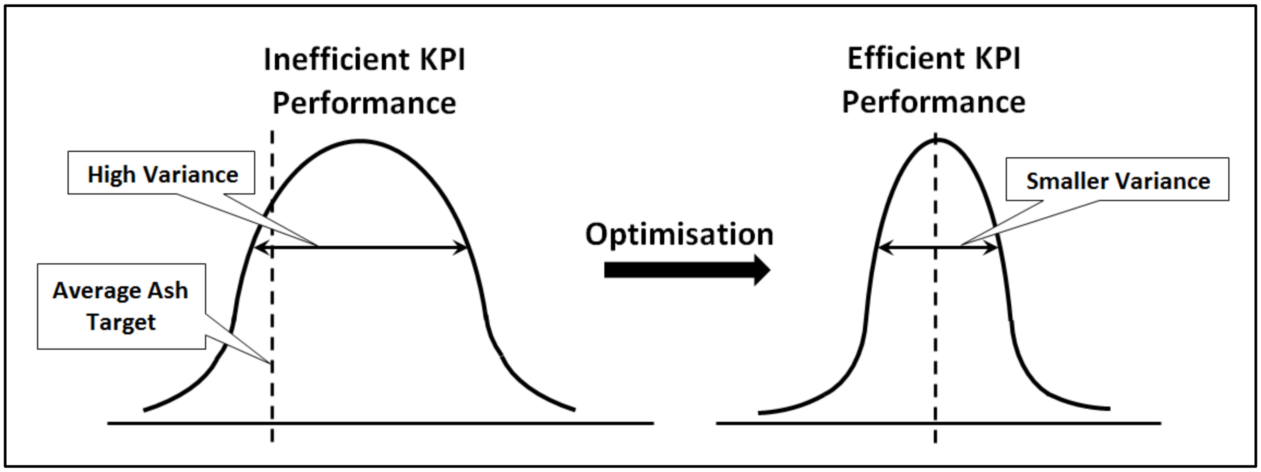

Figure 30: Optimisation objective

The optimisation solution approach for the DMC beneficiation area at GG1 is illustrated in figure 31. The structure of the investigation follows this approach.

5. Data and task discovery (chapter 4): Defining the problem statement, project objective, and discovering and extraction of the relevant data.
6. Data pre-processing (chapter 5): At first, data transformation and integration entail the construction of a data warehouse from which the preceding steps will build on. The data summarisation and data cleaning involve introducing "clean", representative data with high quality to the data mining stage.
7. Data mining (chapter 6): Involves the accurate modelling of the process on data representative of the process dynamics. This stage includes the training and evaluation of the model.
8. Benefit estimation (chapter 7): Include generating the benefit estimation solution, conducting sensitivity analysis for optimal quality control simulations, and discussing the benefits for such an optimal quality control compared to the current control strategy.

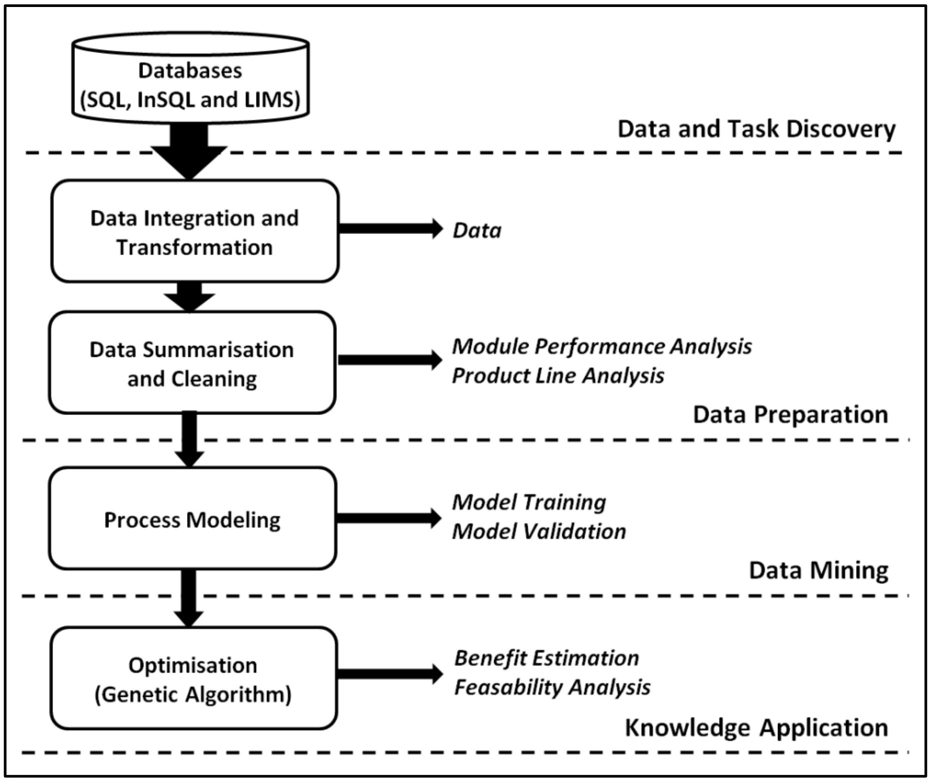

Figure 31: Optimisation solution approach for GG1 DMC beneficiation

4.2 DATA DISCOVERY

After the identification of the problem environment, the data discovery was confined to data from the DMC beneficiation area at GG1. As shown in the process flow diagram (Appendix A), the GG1 plant consists of multiple sensors in the different GG1 areas from where data was gathered. The time range chosen for the data acquisition was from 2009-02-02 17:56:11 to 2010-02-02 17:56:11. The selection of the time range was for the reason that the more data available for analysis, the higher the retention of good quality data and more representative the data, thus increasing efficiency of the KD.

After an extensive data assessment, numerous data attributes (obtained during the period mentioned) were found to be inaccurate. The RD readings measured by the nuclear RD sources in the five modules in AREA04 reported a constant value of 1.5 for a year. After confirming the erroneous readings with a senior metallurgist and a system specialist at GG, the data period was shifted to 2007-07-01 00:00 to 2008-07-01 00:00.

The RD sources records from the time showed accurate measurements for AREA04 modules.

The RD set point values for the separation density of the DMCs in the AREA04 showed some inaccuracies. After investigations as to why these readings were inaccurate, the tag names were found to be incorrect. The correct tag names comprising the correct set point values were acquired within the adjusted period.

The KD process is an iterative process in the sense that with additional knowledge gained from each step, the user may return to a previous step to alter data for more accurate analysis. This is the case with the period identification. During the data-cleaning step, the time range was found to be too large and the analysis became time consuming.

In order to reduce the amount of data whilst keeping the credibility of the data, the data were classified into good quality and bad quality stockpiles. Within a year’s time (2007-07-01 00:00 to 2008-07-01 00:00) the GG1 plant managed to stack 145 semi-soft coking coal stockpiles.

In conjunction with the objectives of the investigation, 21 stockpiles (three groups of seven sequential stockpiles) were chosen representing the process dynamics the best and enabling the accurate evaluation of the investigation results. This stockpile selection depended on two selection boundaries: seven sequential stockpiles with the average ash content closest to 10%, and with the greatest cumulative weight. The reason for the three groups of sequential stockpile data is to compare the analysis results of the groups for more extensive knowledge extraction, as well as better data representation. Table 7 gives a summary of the groups of stockpiles selected, as well as the properties of each of the stockpiles within the respective groups. The time range summarised in the table will serve as the analysis time range.

Table 7: Summary of stockpile selection[18]

Stockpile Name	Stockpile number	Average Ash	Cumulative Tons
Group 1	Time Range:	11/19/2007 21:40:00 to 12/6/2007 15:00:00	
2K02692	43	10.41	18007.00
1K02693	44	10.20	25110.52
2K02694	45	10.54	27785.65
3K0695	46	10.30	70.00
3K02695	47	10.29	14763.38
4K02696	48	10.42	28349.63
NK02697(emergency stockpile)	49	10.16	6436.33
Group 2	Time Range:	12/31/2007 21:45:00 to 1/21/2008 8:00:00	
1K02704	56	10.46	22841.07
3K02705	57	10.53	23937.55
2K02706	58	10.31	18779.24
1K02707	59	10.42	26735.97
2K02708	60	10.30	23931.70
3K02709	61	10.50	25733.84
2K02710	62	10.22	7969.79
Group 3	Time Range:	5/23/2008 5:36:00 to 6/11/2008 14:40:00	
4K02772	126	10.13	14494.10
1K02773	127	10.45	20039.02
3K02774	128	10.48	14809.00
1K02775	129	10.07	11194.79
3K02776	130	10.22	20364.84
1K02777	131	10.44	27348.70
3K02778	132	10.18	25482.44
NK02779 (emergency stockpile)	133	9.22	4077.00

[18] 20 minutes were added before each group to compensate for the delays that play a major role in the accuracy of the data mining step of the knowledge discovery.

4.2.1 THE INSQL DATABASE

The data measured and logged in the InSQL database are categorised under the following groups: the feeder runners, the belt scales, the silo level measurements, the on-line RD measurements and final product measurements. The database consists of three data sets containing data with dissimilar characteristics: the analogue history data, the discrete history data, and the LIMS database. These data groups are logged in an InSQL database on a central server. The data are logged in the respective data fields with each field consisting of a unique tag name.

The analogue data set hosts all the measured tags (recorded from the sensors illustrated in the process flow diagram in appendix A) containing the actual values, value timestamps, and value qualities. This time-series data matrix includes:

- Belt scale readings on module one to five in AREA02 to AREA04 (measured in tons per hour).
- Level measurements of the silos in AREA02 to AREA04 (measured in level percentage).
- On-line RD values from the correct medium feed to each DMC module in AREA02 and AREA04.
- Readings from the on-line ash monitor positioned on the coking coal product line.
- Belt scales on the coking coal and the power station coal production lines.

Each measurement attribute includes the value logged at a specific timestamp, the quality of the value, as well as the connection quality between the sender of the data and the receiver (InSQL database). The sampling time for these data records is one minute.

The LIMS database hosts the input and output data logged from laboratory analysis. This discrete data set contains the results from the laboratory data analysis, the sampling timestamp, and the timestamp to which the result was logged the analysis method, and the quality of each entry. The sampling timestamps were logged every hour, but the timestamp of the registering of the results differed in some cases. The results from the ash analysis are of importance since these values are used to adjust the bias calculated in the SBS.

4.2.2 THE SBS SQL DATABASE

The purpose of the SBS is to provide decision support information that enables the user to build stockpiles with average coal quality within required specification in order to avoid penalties. The SBS captures real-time data and laboratory data measured by the on-line ash monitor, moisture monitors and belt scales from the LIMS and InSQL databases. All the data information gathered and calculated by the SBS are stored in SQL database. The data logging format is the main difference between an InSQL database and a SQL database.

The SBS has an update frequency of five minutes. Every five minutes the SBS gathers the necessary data from the InSQL and LIMS databases, does the required calculations, and stores the results in different data tables in the SQL database. This SQL database contains over forty different sequential and time series data sets. Through various SQL queries, relevant data are gathered and calculated. The data sets include different reference data attributes with the purpose of integrating multiple data sets within the SQL database and simplify the data acquisition and calculations.

SBS user input data are required for SBS product specifications. These inputs are also stored in the SQL database and include the registration of the stockpiles, the different top and lower ash and mass limits, positive and negative deviation, the planned average ash content per stockpile, and the planned cumulative weight of each stockpile.

The SBS is responsible for processing numerous computations, using the data available in the InSQL and LIMS databases. Real time processing, cumulative computations, hourly calculations, calculations related to shift obligations, and computations incorporating laboratory results are a summarisation of the responsibilities of the SBS. The results of these responsibilities are logged in the SQL database.

The SBS SQL database obtained from GG contains the data from the SBSs managed for GG1, GG2, GG4, GG5 and GG6. For the purpose of this project, only the data relevant to the 10% ash coking coal at GG1 will be utilised. The data acquisition of the SQL data stretches over a timeframe of three years, 2007 to 2010. A summarisation of the required timeframes of the different stockpile groups is included in table 7. The time integration of the InSQL, LIMS, and SQL database, including the data transformations needed for accurate data, is discussed in chapter 5.

CHAPTER 5

DATA PRE-PROCESSING

After defining the problem environment, the project plan, and identifying the data needed for the task, the KD becomes more focused. Due to the large amount of data recovered in the timeframes mentioned in chapter 4, the potential for poor quality data is high. This stage of the knowledge discovery focuses on the process in which data anomalies are eliminated as far as possible in order to retain higher data quality.

The preliminary data mining stage includes the transformation and integration of the raw data into a user-friendly data platform (off-line data warehouse), the identification of statistical data characteristics, and the elimination of remaining bad quality data using data cleaning techniques.

5.1 DATA INTEGRATION AND TRANSFORMATION

As mentioned in section 3.2 setting up a working environment for managing the huge amount of data, is essential for effective and rapid KD from data (Adriaans & Zantinge, 1996). This KD environment includes a central off-line data warehouse from where data are managed and analysed. Instead of browsing through a large number of data tables in different directories, the data warehouse must make the searching and managing of the data in the central station for further data mining easier.

Microsoft® SQL Server is a relational database management system using T-SQL (Transact-SQL) query language for data management. This management system will host the central off-line data warehouse for this project. Microsoft® also constructed a graphical data management tool: Microsoft® SQL Server Management Studio Express. The central feature of this tool is the object explorer, enabling the user to browse, select and act upon objects configured on the server. This tool will be used extensively to configure, manage and administer the data objects in the data warehouse.

For more comprehensive data transformation, the data were exported from the SQL data warehouse to a comma-separated values (csv) file, readable in Microsoft® Office Excel® 2007. Microsoft® Office Excel® 2007 is also able to connect to the SQL Server directly to view the SQL data tables in Excel. Another useful function, used in this stage of the KD, is the import of data from an Excel worksheet directly into a Microsoft® SQL Server database using a linked server.

Time integration and data transfers are easily managed using CSense® Architect. CSense® Architect enables the user to create schematic blueprints, configuring the environment of data inputs, data transformation and data output. Architect is a useful platform for importing data from SQL Server, an Excel worksheet, or numerous other data sources, transforming or editing the imported data, and exporting the altered data to the desired location.

5.1.1 SQL DATA TRANSFORMATION AND INTEGRATION

All the data relevant to the SBS at GG are logged in a SQL relational database. A backup file was created containing all the SBS data up to 2010. From a SQL Server backup file, the data was easily restored in the SQL Server hosting the off-line data warehouse. No additional format modifications were needed on the data sets within the SBS database.

The SBS SQL database contains data describing the stockpile management of all six of the GG beneficiation plants. Only the data from the GG1 stockpile management is applicable to this project. The other main criterion for the desired data is the specified stockpile group timeframes. The data logged outside of the criteria are excluded from the final warehouse architecture. Numerous datasets are found to be irrelevant to the proposed project, and are excluded.

The datasets contained in the SBS SQL database is divided into five different groups: cumulative data information, hourly data information, real-time data information, user input loggings and general informative datasets. The cumulative datasets represents the cumulative information logged from the real-time datasets, such as the cumulative ash percentage per stockpile or the cumulative mass of the stockpile sorted by timestamp or by sequential data entry. The datasets contain the aggregated readings logged in five-minute intervals. These datasets contain a reference attribute “Ref_Ptr” used to link several datasets. The five-minute aggregated readings are rolled up to hourly intervals and stored in the hourly datasets. The purpose of the hourly datasets is to bring the LIMS results into account, since the laboratory results are available every hour. Table 8 summarises the characteristics of the relevant SBS SQL datasets saved in the SBS database on the SQL Server. The Cumulative_Info, Hourly_Info, and Realtime_Info datasets are included in the data warehouse.

Table 8: SBS SQL dataset summary

Dataset	Description
Cumulative_Info	Time-series dataset: cumulative ash and mass calculations per stockpile, as well as target ash for each stockpile updated every 5 minutes.
Element_Product_Info	Time-series dataset: cumulative percentage sulphur content per stockpile and the target sulphur value updated every hour (not available for the coking coal production line).
Final_Product	Informative dataset: include the upper limit, lower limit, and planned ash content of the GG1 stockpiles.
Hourly_Info	Time-series dataset: includes the ash bias calculation results, the LIMS results, as well as the ash and mass hourly measurements per stockpile.
Input_product	Informative dataset: contains GG1 stockpile information such as upper and lower mass limit and positive and negative ash content deviation limits (not available for the coking coal production line).
Product_element	Informative dataset: includes the upper limit, lower limit, and target sulphur content of the GG1 stockpiles (not applicable to the coking coal production line).
Realtime_Info	Time-series dataset: includes5-minute readings from online ash monitor, the ash readings adjusted by ash bias, and the mass per 5-

	minute interval for each sequential stockpile.
Stockpile_Info	Informative dataset: summary of each stockpile produced during the specified period.

In the more detailed data transformation stages, the relevant time-series datasets were saved as csv files and transformed, using Excel. The transformation of the timestamp tags in order to integrate all the datasets using the timestamp attribute as reference attribute, was performed in Excel. The logging of two values at the same timestamp occurred in several datasets. This was the case for when a stockpile stacking finished and the build of a new stockpile initiated. In other cases, erroneous entries were logged at the same timestamp. An investigation into each instance of duplicate entry was conducted and the timestamps were transformed or deleted accordingly. Upon the investigation of the "Cumulative_Info" dataset, stockpile 1k02765 was excluded from the data used for KD because of inaccurate readings relevant to the stockpile.

Some of the tag names were altered for confidentiality and accessibility reasons. The transformed SBS SQL datasets were imported into the warehouse database. During the data transfer from the csv files to the database in SQL Server Management Studio, the timestamps were integrated and re-sampled[19] on a minute interval basis, using a CSense® Architect blueprint. The reason for choosing the minute interval re-sampling was that the data from the InSQL database were logged on a minute interval basis.

5.1.2 INSQL DATA TRANSFORMATION AND INTEGRATION

The format for data logged in an InSQL relational data repository differs from that of a SQL relation database. Data for an InSQL database are logged as a data grouping per timestamp, in other words all the readings from the associated data sources (such as belt scale measurements and RD values) are logged as a group when the timestamp changes. In retrieving the data from an InSQL databases via a query, the explained

[19]Re-sampling is the event where the execution rate of the data is altered to universal time intervals.

logging format is the typical format in which the data is viewed. Table 9 illustrates a typical data logging format of an InSQL relational repository. A list of data tag names is listed at one timestamp instance and the respective values along with the quality attribute at that instance. The quality of the logging is indicated by an integer value of 0 or 1. If the quality is 0, the quality is good. For a value of 1, the logging was erroneous.

Table 9: InSQL data logging format

Timestamp	Tag name	Value	Quality
2007/08/02 05:01:00	BeltScale_A04_M1	60.2	0
2007/08/02 05:01:00	RDpresent_A04_M1	1.35	0
2007/08/02 05:01:00	Silo_A04_M1	34	0
2007/08/02 05:01:00	RDsetpoint_A04_M1	1.42	0
2007/08/02 05:02:00	BeltScale_A04_M1	45.3	0
2007/08/02 05:02:00	RDpresent_A04_M1	5.00	1
2007/08/02 05:02:00	Silo_A04_M1	32	0
2007/08/02 05:02:00	RDsetpoint_A04_M1	1.47	0

The logging or query format used in the SQL data warehouse is illustrated in table 10. In this case, the data is logged per timestamp per data row. The tag names and the quality per tag are organised as dataset headers.

Table 10: SQL data logging format

Timestamp	BeltScale_A04_M1	Quality	Silo_A04_M1	Quality
2007/08/02 05:01:00	60.2	0	34	0
2007/08/02 05:02:00	45.3	0	32	0
2007/08/02 05:03:00	46.7	0	32	0
2007/08/02 05:04:00	42.4	0	30	0

The first step in preparing the InSQL data was to transform the data into SQL format using SQL queries. SQL queries allow the user to write a SQL command using a query language and to retrieve the data corresponding to certain criteria set in the query. Data satisfying the time period criteria (identified in chapter 4) of each belt scale measurement, silo level reading, and RD measurement of the modules in AREA01 to AREA04 were retrieved, using SQL queries, and saved as csv files. The tag names of the data attributes in the analogue dataset were changed[20] for confidentiality and simplicity purposes. Each of these data attributes consisted of a timestamp tag, value tag, quality tag, detail of the quality tag and an OPC quality tag. The quality tags are the main indicator of good or bad quality.

The next step was to evaluate the timestamps of each of these tags and the quality of the tag values, and delete or transform duplicate and erroneous data entries. As mentioned, after evaluation of the data tags, the data logged for July 2007 were inaccurate and all the data for this month were deleted. After transforming the analogue data attributes, the data tags along with the quality of the tag values were integrated and grouped into the different areas on the GG1 plant. The belt scales readings, silo level measurements and RD readings of the modules in the different areas were integrated and re-sampled into a dataset per area. These datasets were stored in separate databases on SQL Server. The AREA04 dataset was copied to the data warehouse database.

The data warehouse database contains transformed and integrated datasets in universal format for a more efficient data-mining environment. The data warehouse includes a central dataset in which all the necessary data are integrated into one dataset: the AREA04 datasets, Cumulative_Info, Hourly_Info, and Realtime_Info datasets. This warehouse database will serve as a central management data source where the data could easily be retrieved for analysis. The rest of the datasets are left in their respective databases and will be used for information purposes only. Table 11 include the tag names and the description of each tag relevant to the investigation. Each tag was renamed for confidentiality and simplicity purposes.

[20] Table 11 shows four of the altered tag names. For example: BeltScale_A04_M1 refers to the belt scale measurement read from module 1 in AREA 04.

Table 11: List of process variables relevant to the investigation

Tag name	Description
Cum_SP_Order	Stockpile number ordered from 1 to 145
	Mass and mass flow measurements
BeltScale_A04_M1 – M5	Belt scale on module 1 to module 5 in AREA 04
CCScale	Belt scale on the semi-soft coking coal product line
PSCScale	Belt scale on power station coal product line
Cum_Tons	Mass accumulation of actual coking coal stockpile calculated in the SBS
Cum_Mass_OPT	Mass accumulation of optimised coking coal stockpile
HR_Tons	Accumulated mass per hour interval, calculated in the SBS.
Opt_Mass	Optimised coking coal mass flow
Target_Mass	Target accumulated mass per stockpile
	Ash Content Measurements
RDPresent_A04_M1 – M5	RD value as measured by RD source on module 1 to module 5 in AREA 04
RDSetpoint_A04_M1 – M5	RD set point on module 1 to module 5 in AREA 04
AshMonitor	Ash content measured by online ash monitor on the semi-soft coking coal product line, sampled in one minute intervals
Online_Total_Ash	The bias updated ash with one-minute sampling rate.
HR_Ash	Accumulated ash content per hour interval, calculated in the SBS.
Opt_Ash	Optimised ash content on semi-soft coking coal product line
RT_Coalscan_Ash	Ash content measured by online ash monitor aggregated in 5 minute samples
RT_Ash	Ash content updated with a bias in the SBS, aggregated in 5 minute samples
HR_Coalscan_ash	Ash content updated with a bias in the SBS, aggregated in 1 hour samples
HR_Lab_Ash	Hourly laboratory results on the ash content.
Target_Ash	Target ash content calculated in optimisation solution
HR_Ash_bias	Bias calculated from laboratory results, updated hourly
Cum_Ash	Ash accumulation per stockpile from actual process
Cum_Ash_OPT	Ash accumulation per stockpile from optimised results

5.2 DESCRIPTIVE DATA SUMMARISATION AND DATA CLEANING

The characterisation of integrated and transformed data focuses more comprehensively on the individual attributes exposing the inconsistencies within these attributes. Using statistical techniques along with the process knowledge gained thus far, the data quality can be purified up to a point where the results of the data mining stage are accurate enough to build a consistent nonlinear model. Anomalies identified by descriptive data summarisation can lead to further data transformation and integration in the data cleaning stage.

After the detection of the inconsistent data identified in this stage, the errors and inconsistencies need to be eliminated. Data cleaning is the KD step prior to the data mining which cleans the data inconsistencies. For a reliable non-linear model the data used need to be cleaned and of good quality.

One of the outcomes of the descriptive data summarisation and integration step is to gain more knowledge on the problem environment. The extent of the knowledge gained in this step is dependent on the data quality and the amount of data. For this reason the timeframe, 2007-08-01 to 2008-06-30, was used for knowledge extraction and stockpile validation.

Prior to the DMC operations, the feeds are graded on the respective sieves. The performances of the sieves are unknown. No measurements (mass or ash related) are logged on the sieves' overflows (+1mm; -25mm) sent to the DMC's or the underflows (-1mm), sent to the thickeners in AREA05. Information on the AREA05 coal beneficiation is also lacking. Coal added from the spirals to the final coking coal product line and the power station coal line, are not measured. Coal input information to AREA05 is also not measured. This lack of information is illustrated in figure 32. The solid lines represent the coal flow of which the information is available and the broken lines represent the coal flow of which measurements are not logged.

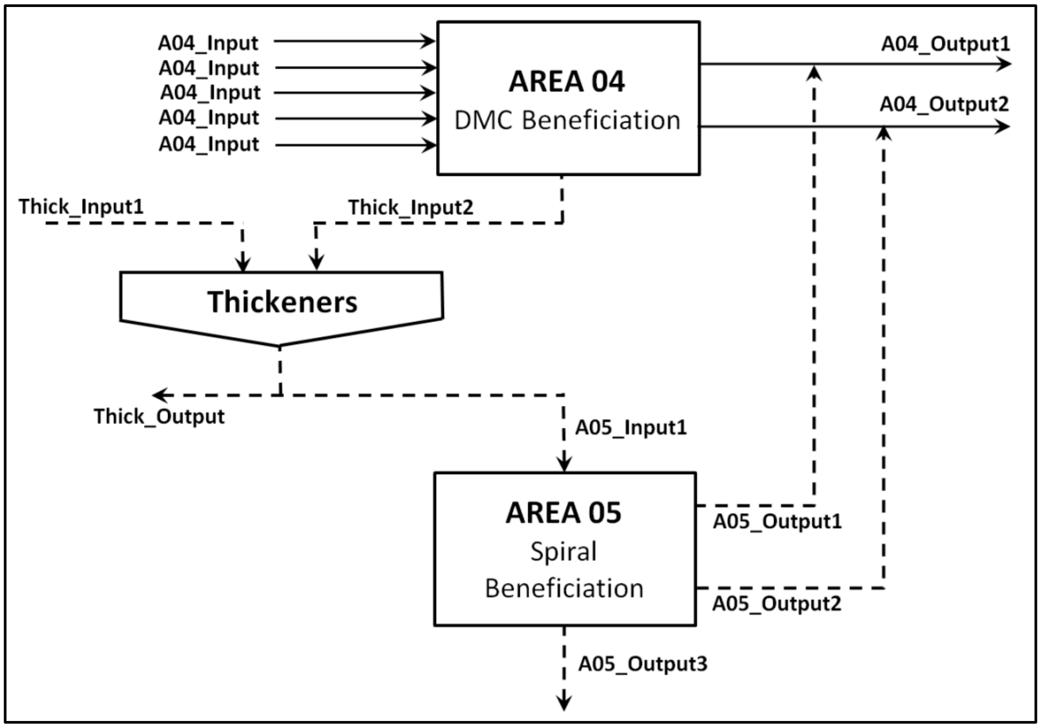

Figure 32: Data flow in the DMC and spiral beneficiation areas.

Table 12 describes the variables illustrated in figure 32. Insufficient information is available to perform a proper mass balance of the process. A list of assumption is given below:

- The AREA04 gradation sieves are assumed to produce negligible -1mm coal for the duration of the analysis period. This assumption effectively excludes the sieves' performance from this study.
- The error produced from the difference between the AREA04 inputs and A05_Output1 and A05_Output2 describe outputs.
- As discussed in chapter 3, typical magnetite losses are attributed to cyclone dimension adjustments. However, a small fraction of magnetite losses are attributed to separation RD adjustments. Magnetite losses are assumed negligible in this study.

Table 12: Data flow tags' descriptions.

Figure 32 variables	Description
A04_Input	Mass flow of the five modules (coal size -25mm) introduced to the gradation sieves.
A04_Output1	Mass flow of DMCs' floats products and spiral coking coal production combined.
A04_Output2	Mass flow of DMCs' underflow products and spiral power station coal production combined.
Thick_Input1	-1mm coal produced in ARE02 and AREA03.
Thick_Input2	-1mm coal produced from sieve gradation in ARE04.
Thick_Output	Coal (-300µm) produced from the deslimer, destined for GG2 beneficiation plant
A05_Input1	Coal (+300µm) product from the deslimer responsible for the input to the spiral beneficiation plant.
A05_Output1	Coking coal production from the spiral beneficiation.
A05_Output2	Power station coal production from the spiral beneficiation.
A05_Output3	Discard from the spiral beneficiation area.

5.2.1 MODULE PERFORMANCE ANALYSIS

This section is dedicated to the summarisation and characterisation of the data variables originating from the five coal modules in AREA04. Data relevant to the five modules are divided up into a mass flow group, dense medium RD measurements and RD set point measurements. The performance of the separation RD control is also summarised in this section.

5.2.1.1 MASS FLOW SUMMERISATION

Figure 33 depicts the mass flow profiles from belt scale measurements. These conveyor belts are responsible for the coal feeds to the DMCs in the five beneficiation modules. During normal operation, it is possible for one or more modules to be offline[21] while other modules are still operational. This operation strategy makes room for maintenance on offline modules while still producing coking and power station coal. The red box in figure 33 illustrates this strategy where module 4 is online and producing coal whilst the rest of the modules are offline and produce small amounts or no coal. In this instance, module 4 will have the highest influence on the final product lines (coking coal and power station coal lines). The DMCs in module 4 will produce higher float mass flows than the other DMCs and thus the product line quality will be determined by module 4's product quality.

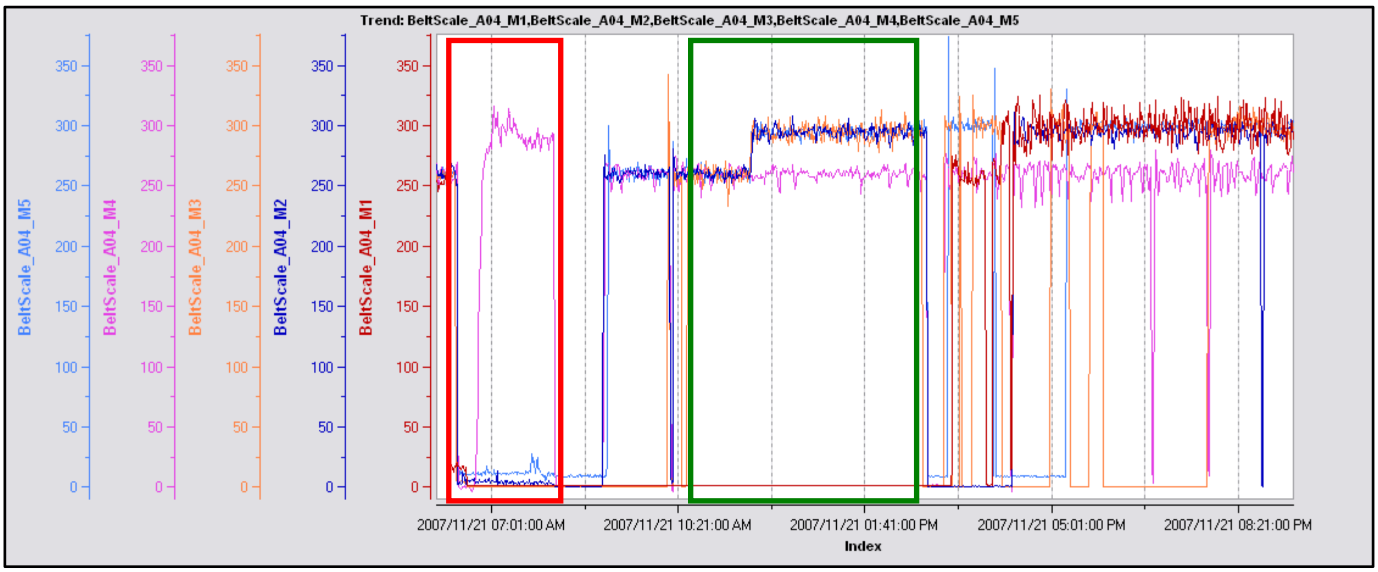

Figure 33: Multiple time-series trends illustrating mass flow profiles to the DMC's.

Also noticeable from the graph are the performances of the different mass flow averages as well as the sudden shift in mass flow averages. This performance is highlighted by the green box in figure 33. Mass flow modules 2, 3 and 5 have a shift from an average of approximately 260 kg/min to 300 kg/min. Module 4 stays on approximately 260 kg/min and module 1 is offline.

[21] 'Offline' in this case refers to a module producing negligible coal product relative to other 'online' modules.

Figure 34 is a scatter plot of the BeltScale_A04_M1 performance on the x-axis and CCScale on the y-axis. Negative mass flow values identified from this scatter plot as well as for the other belt scales were classified as poor quality data and were rejected from certain analyses. The two definite operating clusters, offline and online operations, are visible from this plot. The cluster with mass flows higher than the overall average (represented by the blue line) represents normal online mass flow operation whereas the cluster to the left of the blue line is designated as the offline operation. BeltScale_A04_M1 spent 55.9% of the time in the normal operating region. Higher availability of the module will increase the mass flow to the DMC beneficiation banks. This will effectively mean a higher production throughput.

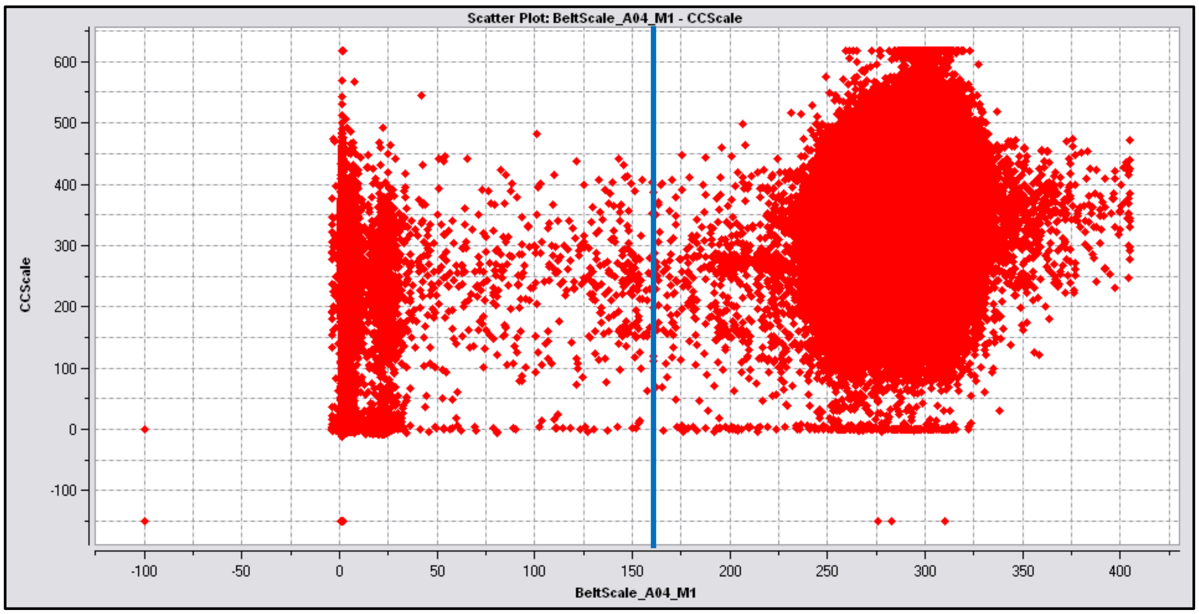

Figure 34: Scatter plot of variables BeltScale_A04_M1 vs. CCScale.

Table 13 summarises the performance of the coal mass flow in AREA04 from 2007/11/19 to 2008/6/11. The minimum and maximum statistics defines the ranges in which the belt scales operate. The ranges include the online as well as the offline data. The average and standard deviation calculations were determined based on online operation only[22].The amount of time spent in the normal operating region (i.e. above overall average operating region) are also calculated for each belt scale.

Table 13: Statistical summarisation of mass flows to the DMCs

Variable Name	Minimum *(kg/min)*	Maximum *(kg/min)*	Average *(kg/min)*	Standard Deviation	Operating time spent above overall operating average*(%)*
BeltScale_A04_M1	0.13	405.02	287.51	20.08	55.9
BeltScale_A04_M2	0.13	405.77	283.25	18.00	54.5
BeltScale_A04_M3	0.13	405.14	286.88	23.40	60.0
BeltScale_A04_M4	0.13	404.05	276.34	62.93	61.8
BeltScale_A04_M5	3.63	403.27	292.62	53.93	55.8

The mass flow feeds to the different DMC banks produced relatively the same performance over the analysis period. BeltScale_A04_M4 produced a lower average feed flow with higher standard deviation during the analysis period.

5.2.1.2 DENSE MEDIUM DENSITY SUMMARISATION

As mentioned in chapter 2, the DMC is the workhorse in coal beneficiation plants. The separation RD's of the magnetite suspension determine the degree of separation among other factors. Figure 35 shows the profiles of the different magnetite RDs measured on each module. The differences in RD measurement variance between the modules are noticeable from this multiple trend. The variance in RDPresent_A04_M1 and RDPresent_A04_M2 are greater than that of the other three RD measures. The reason for this is unknown; however, high RD variance could indicate instability in the magnetite recovery system. A very important characteristic of the RD measured tags at GG1 is the incremental control adjustments brought on by operator set point adjustments. The operator uses a trail-and-error method to control the qualities of the DMC floats in order for the accumulated ash on the coking coal stockpile to reach a

[22]The statistical calculations performed in this study are discussed in appendix D.

predefined quality. The incremental changes are highlighted in the green boxes in figure 35.

As highlighted in chapter 2, controlling the DMCs to produce the same quality goal is the most optimised strategy to maximise revenue produced by a coal beneficiation plant. This crucial feature is depicted in figure 35. The RD's of the dense medium fed to the five DMC banks are controlled on approximately the same RD set points.

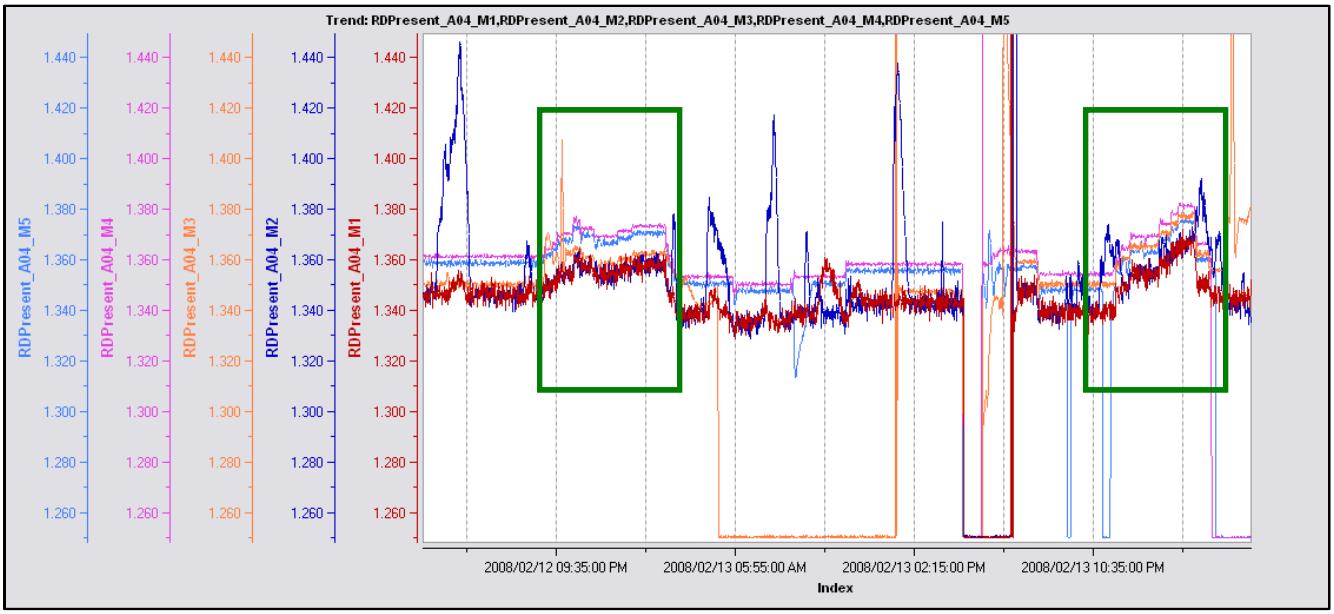

Figure 35: RD measurements for modules on to five.

Table 14: Statistical summarisation of dense medium RDs to the DMCs

Variable Name	Minimum	Maximum	Average	Standard Deviation
RDPresent_A04_M1	1.25	1.45	1.324	0.0493
RDPresent_A04_M2	1.25	1.45	1.331	0.0624
RDPresent_A04_M3	1.25	1.45	1.327	0.0512
RDPresent_A04_M4	1.25	1.45	1.333	0.0552
RDPresent_A04_M5	1.25	1.45	1.326	0.0511

Table 14 summarises the dense medium density performance of the analysis period. The five variable summarised are comparable in the average performance and variance. This is due to the control strategy of the operator to adjust the RD set points to the same degree.

5.2.1.3 RD SET POINT SUMMARISATION

Figure 36 illustrates the performance of the adjustments on the RD set points brought on by the operator. The operator adjusts the RD set points to approximately the same degree. Adjustments to the set points do not occur in a fixed frequency but is dependent on the judgement of the operator. There are periods where the differences in RD set points are greater than other regions. The reason for variance in set points differences are unknown and completed dependent on the logic behind the operator's control strategy.

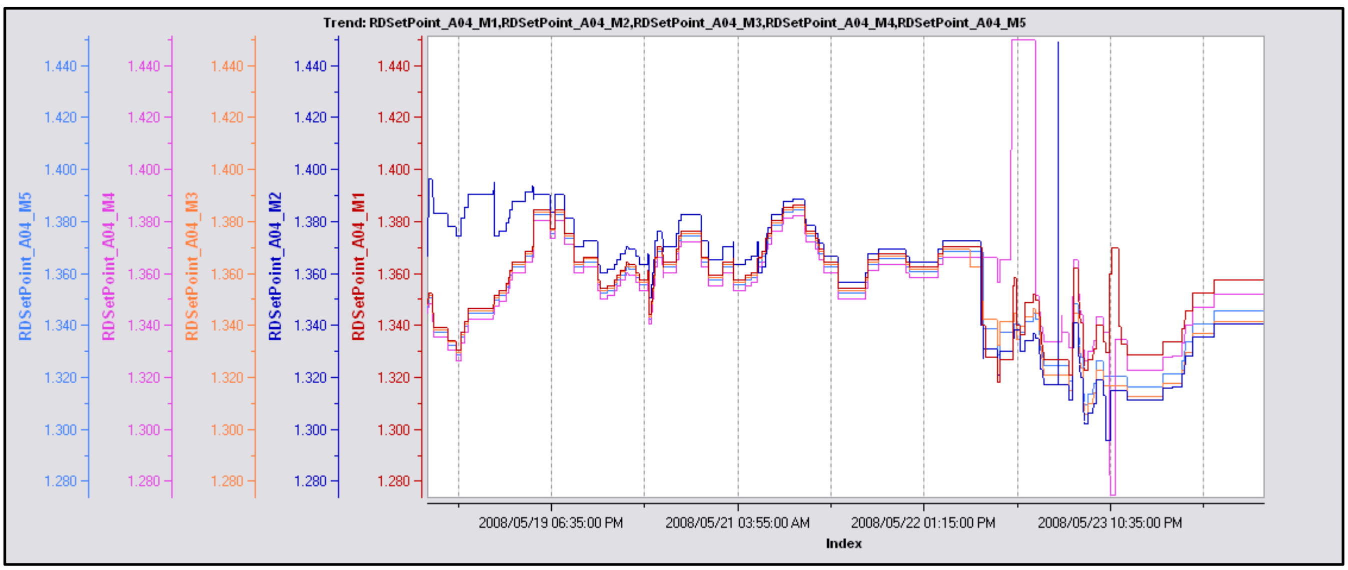

Figure 36: RD set point performances for the five GG1 modules

Table 15 summarises the behaviour of the RD set points on the five modules. The five variables' performance similar due to the operator's set point adjustment logic. When comparing the set point variable standard deviation with that of the dense medium RDs, the dense medium RDs show higher variance. This could to be ascribed to the noise existent in the dense medium RD measurements.

Table 15: Statistical summarisation of dense medium RDs to the DMCs

Variable Name	Minimum	Maximum	Average	Standard Deviation
RDSetPoint_A04_M1	1.25	1.42	1.349	0.0177
RDSetPoint_A04_M2	1.25	1.45	1.357	0.0184
RDSetPoint_A04_M3	1.25	1.42	1.357	0.0169
RDSetPoint_A04_M4	1.25	1.45	1.358	0.0176
RDSetPoint_A04_M5	1.30	1.42	1.355	0.0169

5.2.1.4 DENSE MEDIUM RD CONTROL PERFORMANCE

The performance of the control implemented on the magnetite recovery circuits can be measured through the comparison of the magnetite density set point to the process variable, the magnetite RD. Figure 37 illustrates how good the control performance is on the module 3 magnetite recovery circuit. The magnetite RD measurement is compared to the RD set point. It is important to note the deviation from accurate control in some instances. The green box in figure 37 shows an example of this deviation. These deviations are the cause for disturbances in the quality of the DMC float products. If the operator adjusts a RD set point, the magnetite RD is expected to operate closely around the set point value. In the event of a disturbance, the operator should react on the RD set points and compensate for magnetite RD deviation. This compensation could lead to inaccurate quality control of the product coal. For ideal control, the difference between the magnetite RD and the set point should be zero.

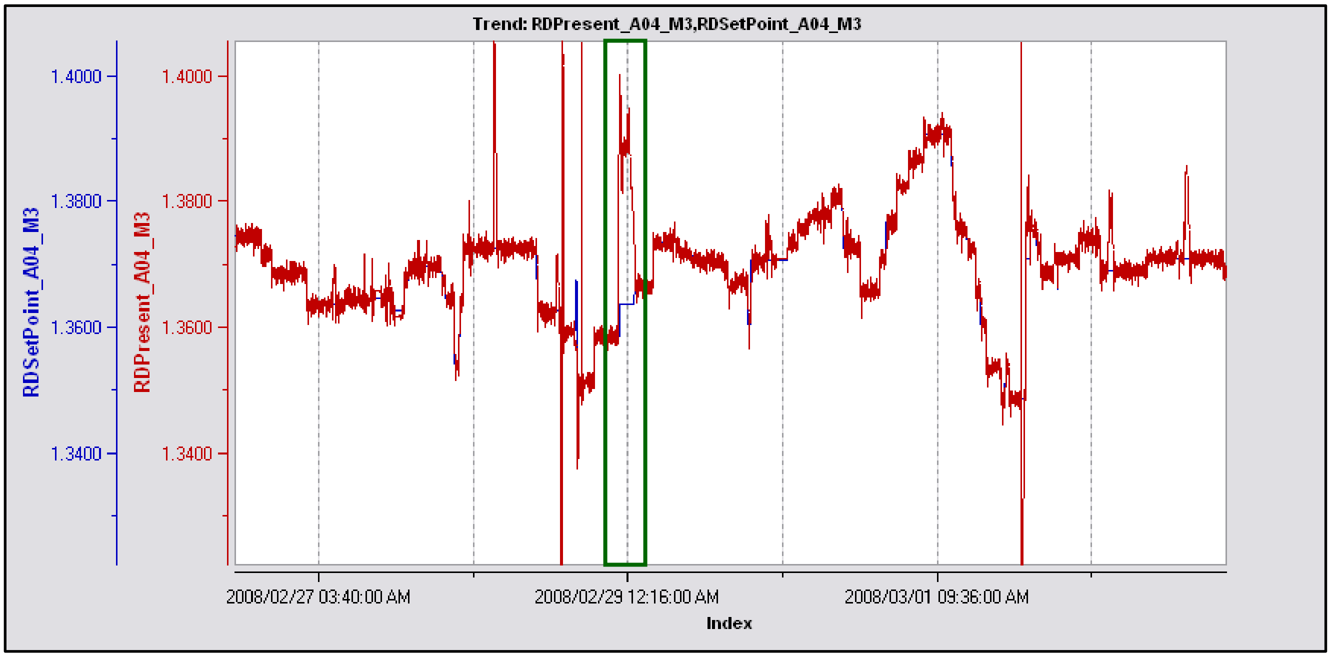

Figure 37: Control performance on magnetite RD on module 3

Figure 38 shows the relationship between the dense medium RD and the RD set point for the magnetite recovery circuit in module 3. A linear least squares fit is also included in the scatter plot summarising the relationship between the two variables. Typically, a horizontal fit will indicate that no correlation exists between the two variables. Figure 38 shows a direct correlation, whereas a negative slope will indicate indirect correlation.

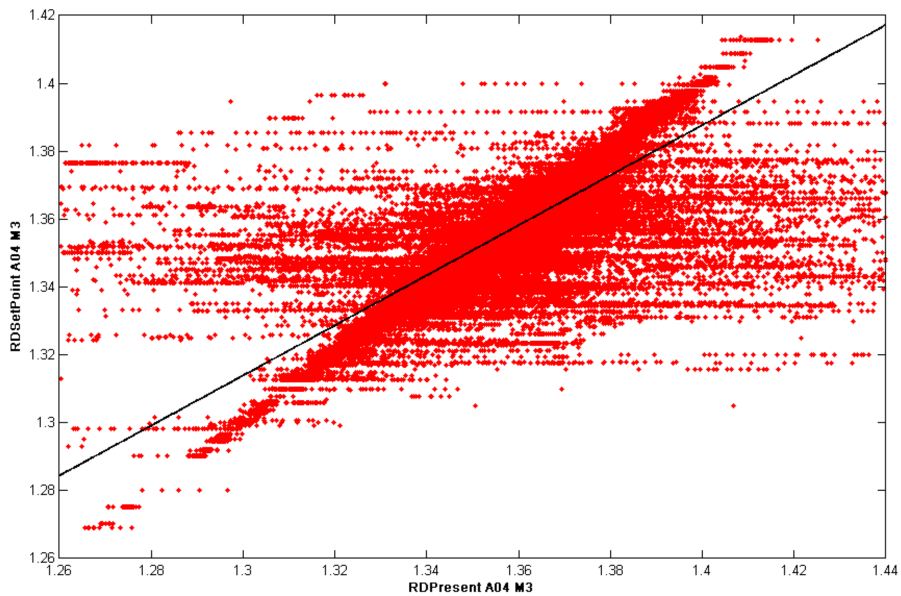

Figure 38: Scatter plot: RDPresent_A04_M3 vs. RDSetPoint_A04_M3.

Table 16 summarises the RD control performances of each module magnetite circuit. The difference between each module's magnetite RD and RD set point were calculated as the RD error. The averages as well as the standard deviation of the error calculations are included in table 16. The correlation between the magnetite RD and the RD set point is also included in the table. Module 3 produced the best control performance with a lower standard deviation and high actual versus set point correlation.

Table 16: RD control summarisation

Module	Error Average	Error Standard Deviation	RD vs. RD Set Point Correlation
RD control in module 1	-0.00215	0.0149	0.683
RD control in module 2	-0.00241	0.0176	0.665
RD control in module 3	-0.00111	0.0091	0.830
RD control in module 4	-0.00312	0.0140	0.740
RD control in module 5	-0.00078	0.0131	0.727

5.2.2 GG1 PRODUCT LINE ANALYSIS

5.2.2.1 LAG ESTIMATIONS

An important data preparation aspect is the estimation of the variable lags, as these time lags play a big role in the accuracy of the time-series modelling, and place rigorous constraints on the performance of an automated control loop. This vital aspect of data preparation is included in the data cleaning stage of the KD process.

The aim of the time lag compensation is to delay the suitable measured variables up to a point where the correlation between the target variable and the process variables is at a maximum. The target fields of the NN models are the supervisory variable needed to create the supervised NN explained in chapter 2. These target fields contain the measurements from the online ash monitor as well as the mass flow measurements on the coking coal product line. All the belt scales, RD set point readings and the RD present values measured by the RD sources, must be delayed up to the point where their correlation to the target variables are at a maximum.

Cross-correlation based lag estimation was used to determine the different time lags for the relevant process variables. In order to estimate the time lag for a process variable the non-target process variable is delayed incrementally with a time constant and the correlations between the fixed and delayed variables are determined.

Figure 39 illustrates the cross-correlation calculation performed on the mass flow measurement taken from module 2. The mass flow measurement was delayed with nineteen minutes with a time constant of one minute. The correlation between the coking coal mass flow and the mass flow measured in module 2 is at a high at a two-minute delay. This effectively indicates that a step change in mass flow in module 2 will be visible on the coking coal product line mass flow measurements after 2 minutes.

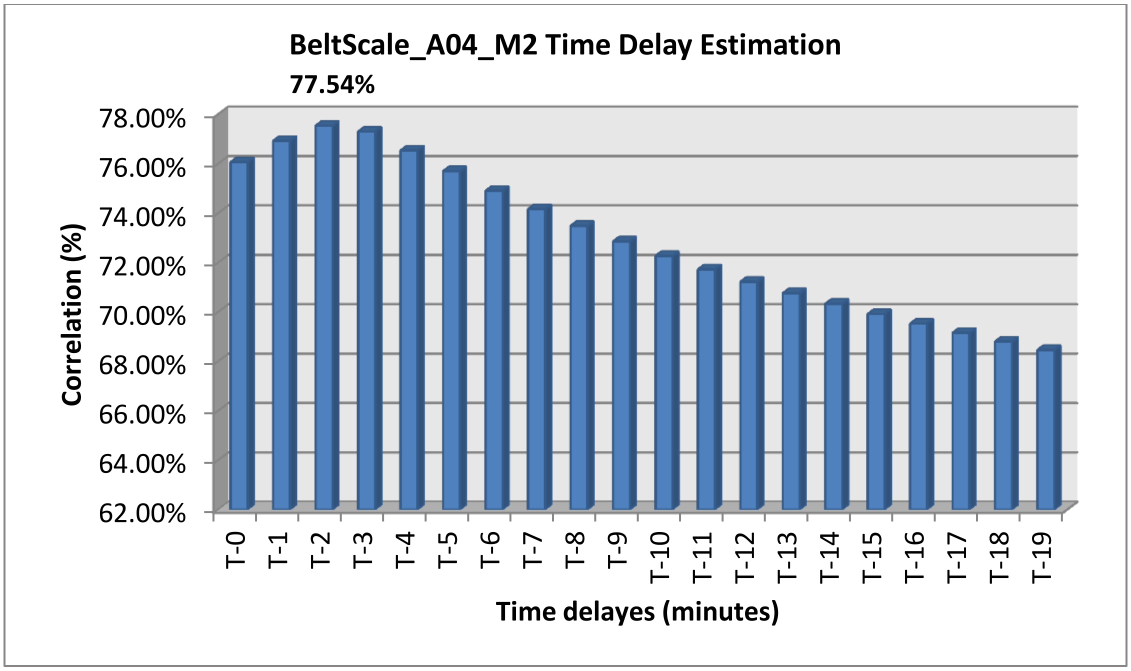

Figure 39: Time Delay Estimation of BeltScale_A04_M2

Table 17 represents the results from the constant time delay estimations for the module belt scales measurements and dense medium RD measurements. Evident from these results is that time lag between the module mass flow measurements and the coking coal product line mass flow is two minutes with a high degree of probability. It will be safe to keep the time delay as a constant time delay of two minutes without affecting the quality of the data.

As for the constant time delays estimated for the ash content (time lag from magnetite RD measurements in each module to the on-line ash monitor), the correlation is very low. In addition, the time delay at maximum correlation for each module differs. Thus, a constant time lag cannot be calculated for the magnetite RD measurements. As indicated in section 4.1.1, experts at GG1 assume the time lag to be a constant fifteen minutes (Rautenbach, 2009a). The time lag for the magnetite RD measurements to the ash monitor measurements is assumed fifteen minutes for this study.

Table 17: Constant time delay estimations

	Maximum Correlation (%)	Time Delay (seconds)
	Mass Flow	
BeltScale_A04_M1	75.14%	120
BeltScale_A04_M2	77.54%	120
BeltScale_A04_M3	76.83%	120
BeltScale_A04_M4	64.74%	120
BeltScale_A04_M5	65.13%	120
	Ash Content	
RDpresent_A04_M1	2.59%	780
RDpresent_A04_M2	3.13%	780
RDpresent_A04_M3	4.58%	780
RDpresent_A04_M4	3.14%	720
RDpresent_A04_M5	2.50%	1320

5.2.2.2 COKING COAL PRODUCT LINE ANALYSIS

Characterisation and summarisation of the product line data were done on cumulative, hourly, and real time data (five-minute interval sample rate). The cumulative data are summarised in table 7 in section 5.7.

The reason for storing hourly data in the SBS SQL database is for the integration of the laboratory results. As discussed in section 2.4.4 spot samples are taken every hour and sent to the laboratory for detailed analysis. The results are delayed with approximately four hours. Figure 40 illustrates the performance of the ash measured directly from the ash monitor (HR_Coalscan_ash), the ash updated by the ash bias (HR_Ash), the ash bias calculated in the SBS (HR_Ash_bias), and the ash results from the laboratory (HR_Lab_Ash). It is interesting to see the offset of the HR_Coalscan_ash variable from the HR_Ash and HR_Lab_Ash variable. As indicated in chapter 2, from expert knowledge on the process at GG1 it is known that the online ash monitor does not produce accurate measurements. This is evident in the offset between the laboratory results and the online ash monitor measurements. The average of the HR_Coalscan_ash variable is 11.23% compared to the 10.32% and 10.33% of the

HR_Ash and HR_Lab_Ash variables respectively. The reason for the HR_Ash performing in the same range as the HR_Lab_Ash variable is the Ash_bias update.

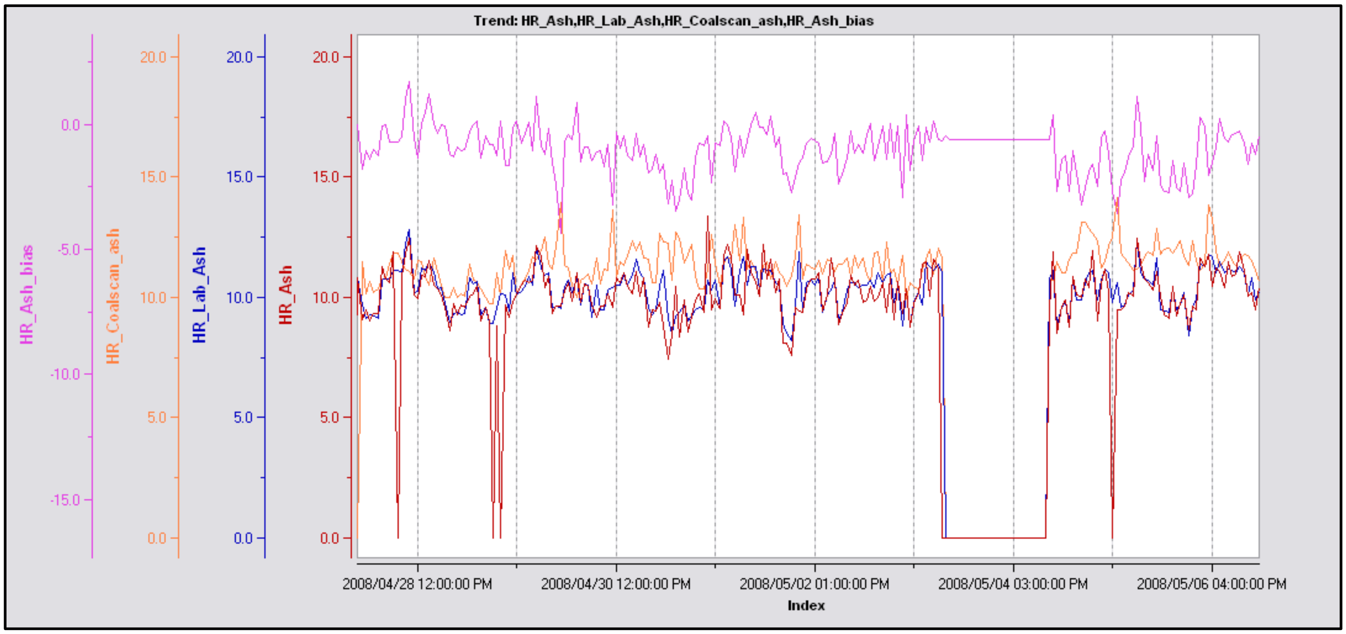

Figure 40: Hourly ash content data stored in SBS SQL database

To determine the accuracy of the bias updated ash measurements, the relationship between the variable need to be evaluated. Table 18 is a correlation matrix containing the correlation between the three hourly ash measurements. The relationship between the HR_Lab_Ash (which is the more reliable ash content measurement) and HR_Coalscan_ash are comparable to the relationship between HR_Lab_Ash and HR_Ash. From the correlation matrix it can be concluded that the dynamics of the ash measurement updated with the bias are relative the same when analysing the system with an hour sample rate.

Table 18: Hourly ash measurements correlation matrix

Variable Name	HR_Lab_Ash	HR_Ash	HR_Coalscan_ash
HR_Lab_Ash	1.000	0.887	0.857
HR_Ash	0.887	1.000	0.840
HR_Coalscan_ash	0.857	0.840	1.000

Figure 41 compares the bias (HR_Ash_bias) updated ash content measurements (RT_Total_Ash) to the online ash monitor measurements (RT_Coalscan_ash) with the sampling rate of five minutes. Again the RT_Coalscan_ash shows an offset relative to the RT_Total_Ash) measurements. However, the correlation between the two variables stays high at 0.827.

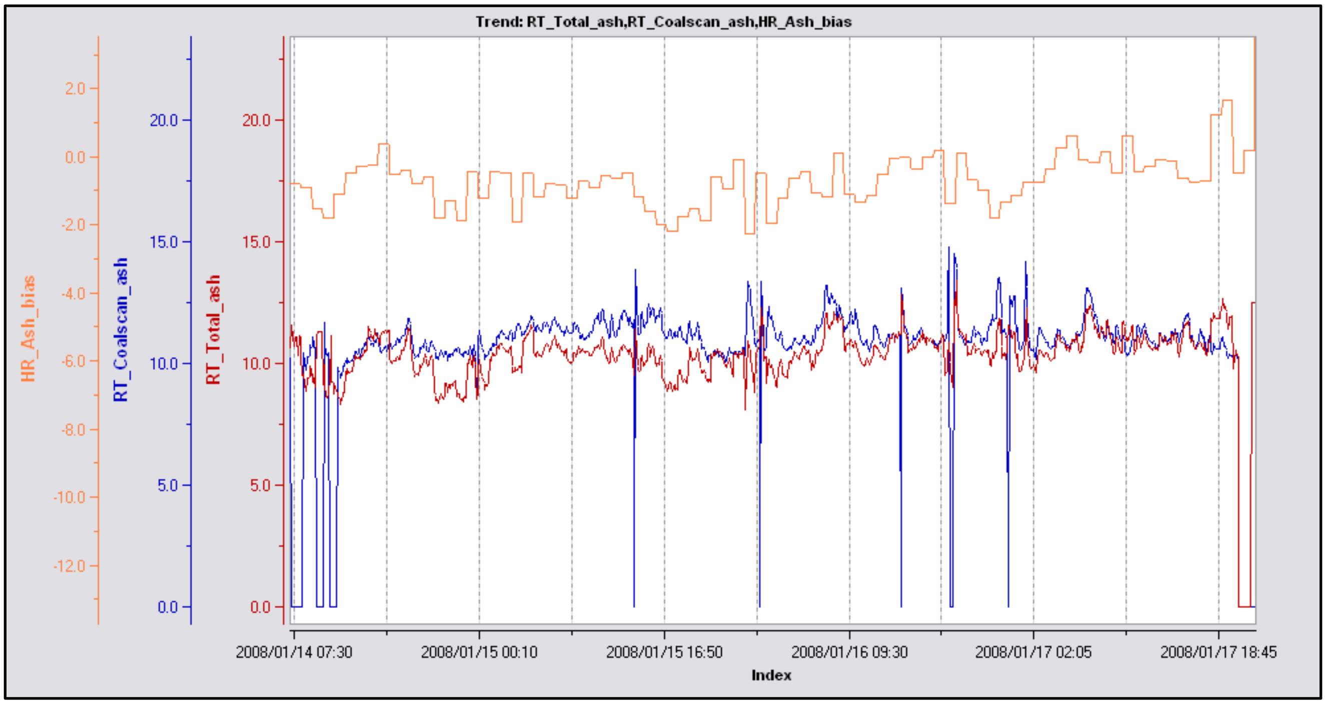

Figure 41: Ash content variable comparison - five-minute sampling rate

Timestamp integration of the datasets is necessary in order to integrate the InSQL data (one-minute sampling rate) with the real-time data from the SBS (five-minute sampling rate). Essentially this step requires SBS dataset transformation to produce a dataset with a one-minute sample rate, the same as the InSQL dataset. The difference between the hourly ash bias and the one-minute online ash monitor readings was calculated to generate the bias updated ash variable with a sampling rate of one-minute.

Figure 42 shows the accuracy of the calculations performed to determine the ash content updated with the bias on a one-minute sampling rate. Both RT_Total_Ash and Online_Total_Ash are bias updated ash measurements with a correlation of 0.862 during normal operation. The correlation between the online ash monitor data and the

Online_Total_Ash variable is 0.969. The AshMonitor and RT_Coalscan_ash variables are generated directly from the online ash monitor with different sampling rates. An offset between the online ash values and the bias updated ash values is still visible.

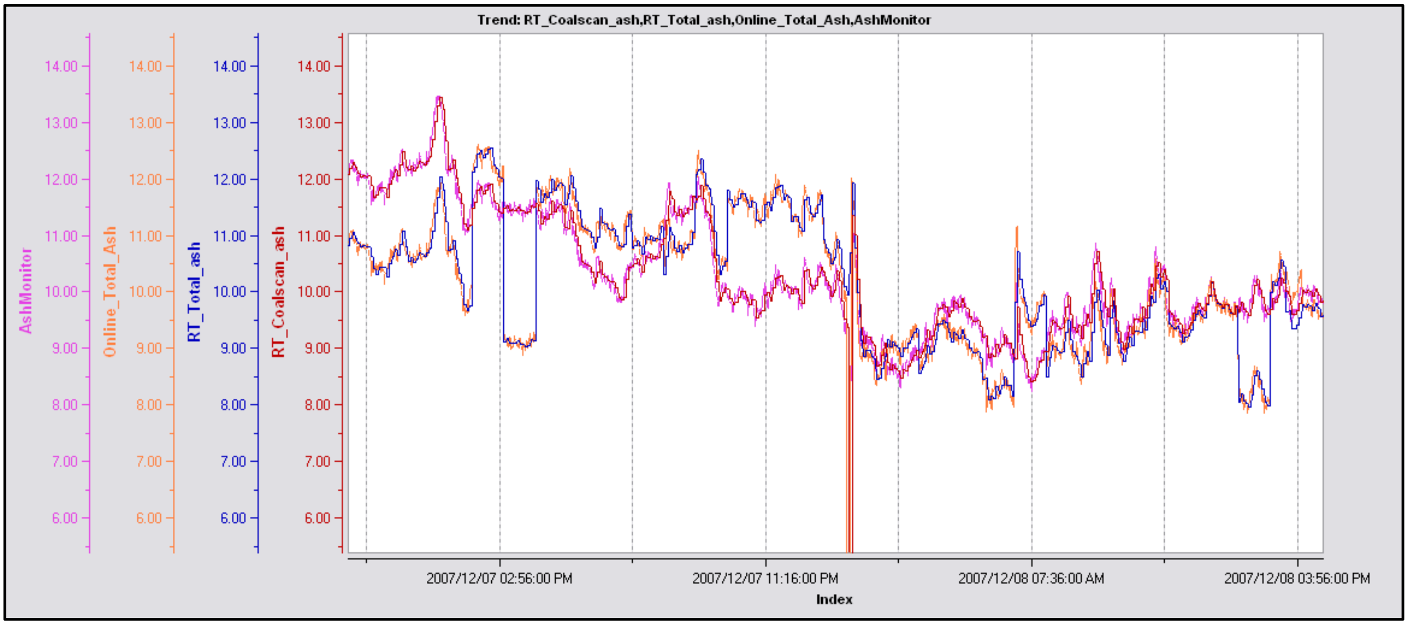

Figure 42: Ash monitor measurements vs. bias updated measurements

An important characteristic exists in the relationship between the mass flow on the coking coal product line and the ash content of the coking coal. Figure 43 shows the relationship between the two product line variables CCScale and Online_Total_Ash. Three distinct data clusters are visible from this scatter plot. The cluster encircled with green represents normal operation. The two clusters above and below the normal operation cluster represents offline operating conditions. It is important to define the offline and online regions when considering the training of the NN model (discussed in the next chapter).

Figure 44 illustrates the online and offline operation of the mass flow and ash content[23] of the coking coal product. The grey highlighted regions in figure 44 represent the

[23]The Ash_Monitor variable was trended instead of the Online_Total_Ash variable, because the Ash_Monitor contain data directly measured from the online ash monitor and will show offline instances better than the Online_Total_Ash variable, which is a calculated variable.

cluster identified in figure 43 highlighted in green. Evident from figure 44 is the offline instances represented by the white regions. In some cases, unusually high ash content measurements are associated with offline mass flow readings. In most instances, both the mass flow and ash content readings are zero or close to zero indicating the process being offline.

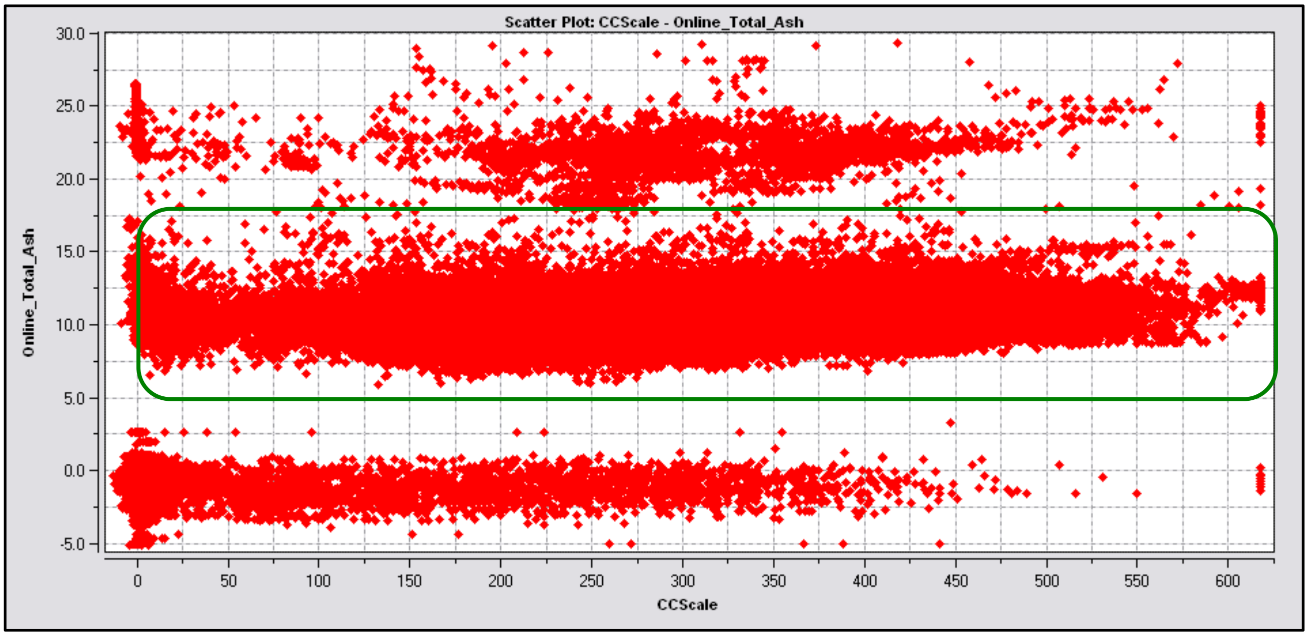

Figure 43: Scatter plot: Coking coal mass flow vs. coking coal ash content

Notice the operation of the module variables during online process operation illustrated in figure 45. The grey regions on the figure represent online process operation. While the process is online, i.e. while the mass flow and ash content measurements produce normal results, a module may be offline. The NN model would need to account for offline modules instances.

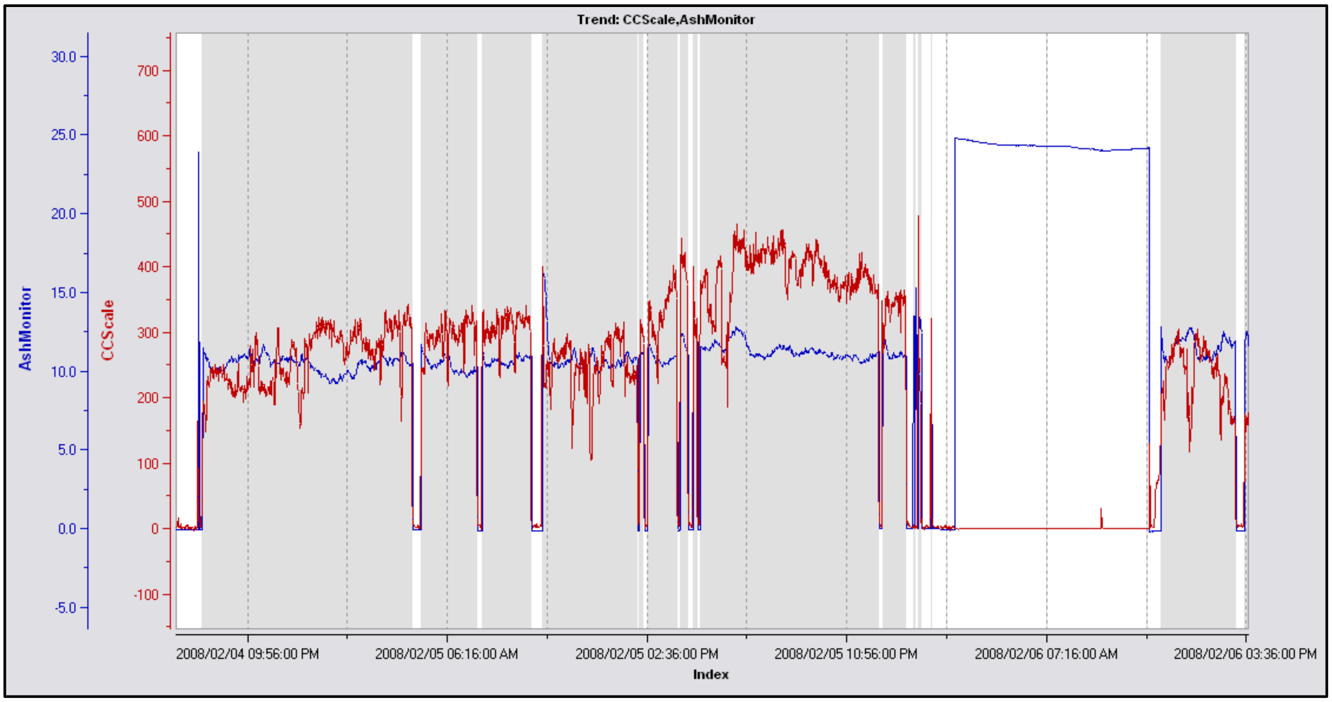

Figure 44: Online and offline product variable operation

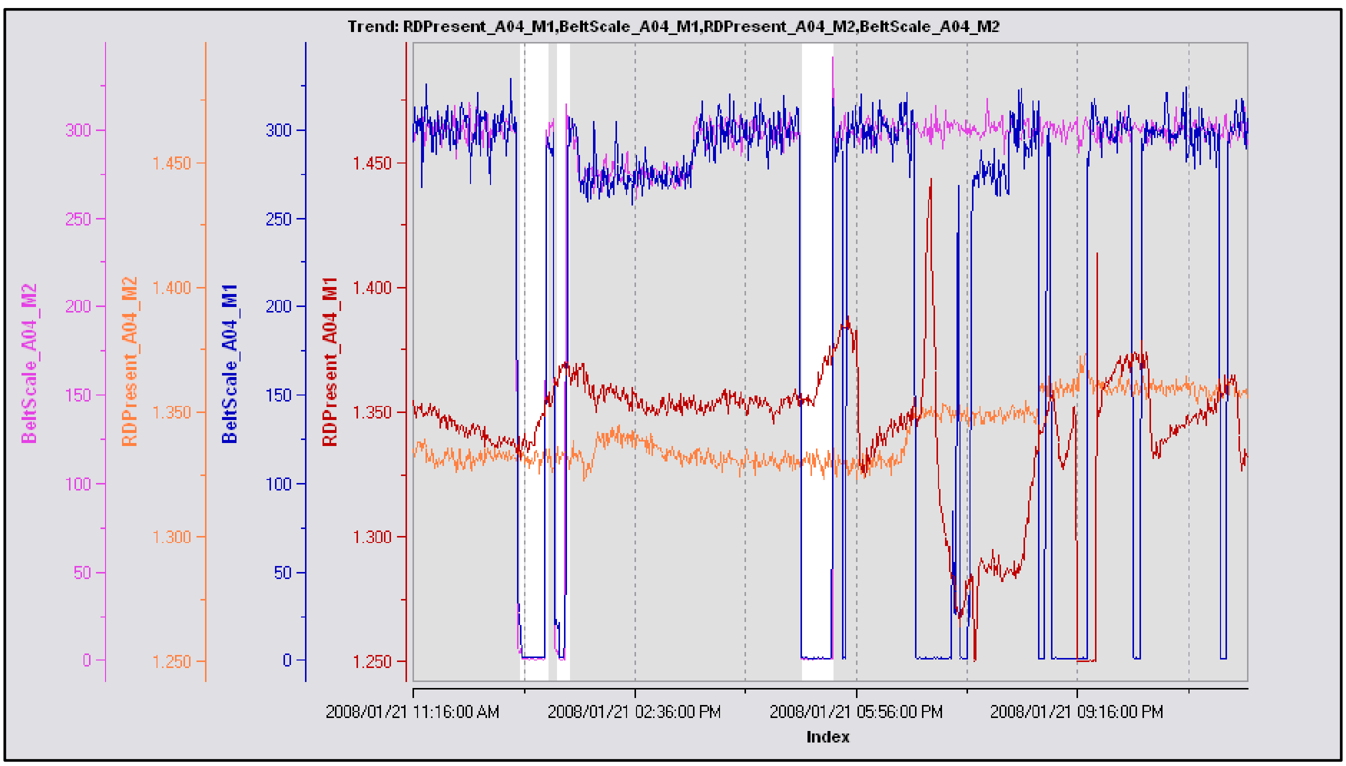

Figure 45: Module mass flow and magnetite RD offline performance

5.3 CONCLUSIONS

Chapter 5 focused on the process in which data anomalies were identified and eliminated as far as possible in order to retain higher data quality. Several steps were followed during the data pre-processing to produce a dataset containing high quality data. This dataset was populated into the data warehouse defined as the data source for the following KD stages.

The descriptive data summarisation and characterisation section focused on detailed data analysis, including analysis on AREA04 module performance as well as analysis on measurements taken from the coking coal product line. A summary of conclusions are listed below.

1. The mass flows measured before coal enters the DMCs on each module show relatively the same performance.
2. The operator uses a trail-and-error method to control the coal quality on the product line. This strategy was visible when comparing the set point performances as well as the magnetite RD operation.
3. Section 2.3 discussed an optimised DMC control strategy indicating this strategy should aim to control the DMS quality output to produce the same quality. The operator controlling the magnetite RD set points follows this strategy. The operator in most cases adjusts all five set points to the same degree in order to produce similar DMC float qualities.
4. The control efficiency of the magnetite recovery circuits on each module shows good performance with high correlations between the set points and the process variable – the magnetite RDs.
5. The variable lags in the process were determined for the mass flow in the system but not for the coal ash content. The lag for the ash content is assumed fifteen minutes. The lag for the mass flow was calculated at two min. The time lags were incorporated into the data warehouse dataset.
6. The ash content updated with a calculated ash bias was integrated with the InSQL data with one-minute sampling rate. High correlations exist between the bias updated ash content with a one-minute sampling rate (Online_Total_Ash)

and the actual ash monitor measurements (AshMonitor) and the hourly ash content updated by the ash bias (RT_Total_Ash). Better quality control is possible when increasing the frequency of set point updates.

CHAPTER 6

DATA MINING

6.1 INTRODUCTION

Chapter 4 mentioned the integral role a process model plays in the optimisation of the process. NNs were evaluated as a reliable data mining technique as described in chapter 3. The NN introduces high accuracy to data mining, as this technique is able to approximate complex and non-linear process mappings. The NN will be responsible for accurate simulation of the AREA04 beneficiation process.

The actions taken in the preparation stages leading up to the data mining step gave an understanding of several underlying process features. Chapter 4 contributed to the focus to the objectives and relevant data for this study. Chapter 5 was responsible for the characterisation of the relevant data as well as the preservation of reliable data. The goal of chapter 6 will be to integrate the gained knowledge mentioned with the non-linear model prior to the optimisation stage. Chapter 6 discusses the NN input space and results of the trained NNs. The most accurate model will be used for optimisation and benefit estimation.

CSense® software was used during the training and validation of the models. The software allows for the generation of NNs with two hidden layers in the NN topology. The supervised back-propagation training algorithm is used during the training of the NNs.

6.2 NEAURAL NETWORK DATA PREPARATION

As mentioned in chapter 3, the purpose of the research is to investigate the possibility of an optimised control strategy for the DMS separation densities in the five modules located in AREA04. Design and deployment of optimised and control systems depend on accurate process models. Empirical models do not always have the capacity to simulate the dynamics of the process accurately due to model assumptions and lack of knowledge of inter-variable relationships. It is for this reason the NN, a multi-variable modelling technique, is investigated as a possible multiple DMCs process model. The NN is a popular modelling technique due to its ability to detect variable interactions in a complex domain and accommodate data noise and missing data in the model. The NN is also a popular data mining technique used to discover patterns in process data.

An important consideration in choosing a training set for generating an efficient model is the degree of process representation of the dataset. The data used for model generation should be representative of the process dynamics and characteristics. Unfortunately, the data tags obtained from the problem environment give limited understanding of the process. Information such as module sieve efficiencies, relevant information from AREA05 as well as how AREA05 operation influences the performance of AREA04 are important, though missing information. Fortunately, a key feature of a NN is its ability to accommodate missing information.

As described in chapter 4, three groups of data were identified as the datasets with the highest potential in accurately predicting the target variable. Thus, the timeframes of the training datasets are fixed. The inputs should describe the process dynamicity of the process as best as possible. Selecting the input space is not an arbitrary process but input selection should consider an accurate characterisation of the process. A high dimensional input space could over-complicate the model. Another issue to account for is adding to much noise because of unnecessary inputs in the input space. On the other hand, leaving out valuable information contained within data not included in the input space will decrease the accuracy of the model.

Two groups of data exist when considering a process optimisation approach: dependent and independent variables. Dependent tags represent the tags that depend on the operation of the other variables within the optimisation system. For instance, the Online_Total_Ash variable depend on the magnetite separation RDs as well as the module belt scales. Independent data attributes explain the performance of data not depending on other data tags in the system. The module belt scales are examples of independent process variables. The independent tags group consists of adjustable variables as well as state variables. The adjustable variables are the separation RD variables adjusted by the operator via set points. Variables explaining the operating condition of the system are defined as state variables. The ash bias is an example of a state variable as degree of inaccuracy on the online ash monitor is described by the ash bias. However, the ash bias is not an adjustable variable. The two dependent variables relevant the system under investigation is the variables measured on the coking coal product line. The coking coal ash content and mass flow will be the targets of two separate models.

The typical characteristics of the RD set point tags, the actual dense medium RDs, as well as the relationship of the set points to the actual process values were discussed in section 5.2.1. Each module's actual dense medium RD is dependent on the performance of the associated RD set point. However, the performance of the actual dense medium RD contributes to the ash content in the floats product from each DMC, irrespective if this RD deviates from the set point value. The performances of the dense medium RDs of each module are independent of each other. Another characteristic regarding the RD control is that in ideal conditions the set point and the process variable should be highly correlated. The actual RD, however, deviates from the RD set point from time to time. The influence of a module's set point on the product line ash content relies on the actual RD performance. The set point and actual RD value relationship could be simulated using control transfer functions. However, for this study the set points will not be included in the input space. In excluding the set points, the complexity of the NN is decreased as well as the possibility of system noise.

The more tags explaining valuable information regarding the process the better. However, two tags explaining the same information is unnecessary. Highly correlated independent tags explain the same variance in the system and thus including both tags would only add noise to the system. The relationship between the mass flow of the coking coal product line and the power station coal product line is an example of this redundancy. The correlation between the coking coal mass flow and power station coal mass flow is 0.9164. Thus, the power station coal performance will not be included in the models' input spaces. Because the mass flow of the coking coal is dependent on the rest of the inputs in the input space, it will be necessary to be able simulate the mass flow's performance. A second model will be responsible for explaining the mass flow.

The ash bias explains a crucial aspect of the variance in the final ash content of the coking coal. The ash bias variable is a function of laboratory results as well as the error on the online ash monitor. Predicting laboratory results as well as the error on the online ash monitor is not possible since these variables are independent from the process variables. Thus, it is assumed that the ash bias as calculated during the data period (2007/11/19 – 2008/06/11) is fixed during analysis. This effectively means that no matter what the values are from the online ash monitor or the laboratory spot analysis, the error will stay the same.

The real time information available from the SBS SQL database (with a five-minute sampling rate) is calculated from the online data values (with a one-minute sampling rate). During NN testing runs prior to the actual generating of process models, the accuracy of a model trained with the real time info (RT_Total_Ash; RT_Total_Tons) and a model trained without the real time info were compared. The model with a higher accuracy included the real time info. The reason for higher accuracy is the valuable information this tag adds to the system. This real time info tag keeps a five-minute memory of the ash content performance. The memory adds necessary information about the momentum of the ash content performance. RT_Total_Tons and RT_Total_Ash are included in the input space as calculated values.

Table 19 is a correlation matrix summarising the relationships between the variables included in the input space of the ash model as well as the mass model. The mass measured on the coking coal product line is not included in the ash model input space. In turn, the ash calculated for the representation of the ash content on the coking coal product line is not included in the mass model input space. Important to notice for the correlation matrix are the relationships between the input variables and the model target variables. Most of the input variables to the ash model are indirectly correlated to the target variable. On the other hand, all the input variables for the mass model are directly correlated to the target mass variable. The relationships between the variables in the nonlinear multivariate system are discussed in section 6.4.

Table 19: Model input space correlation matrix

	BeltScale_A04_M1	BeltScale_A04_M2	BeltScale_A04_M3	BeltScale_A04_M4	BeltScale_A04_M5	RDPresent_A04_M1	RDPresent_A04_M2	RDPresent_A04_M3	RDPresent_A04_M4	RDPresent_A04_M5	Ash_Bias	RT_Total_Ash	RT_Total_Tons	CCScale	Online_Total_Ash
BeltScale_A04_M1	100	56.6	51.5	62.6	51.3	51.0	33.7	42.7	41.5	43.9	5.9	53.7	49.5	**73.7**	**-25.8**
BeltScale_A04_M2	56.6	100	57.4	65.4	58.9	32.6	61.0	43.0	44.3	49.7	11.9	60.8	38.5	**76.8**	**-29.7**
BeltScale_A04_M3	51.5	57.4	100	64.9	60.1	30.3	43.7	67.5	45.8	53.7	1.2	59.2	57.7	**79.1**	**-29.9**
BeltScale_A04_M4	62.6	65.4	64.9	100	72.1	40.1	49.6	57.7	56.2	61.9	6.1	67.6	54.6	**85.1**	**-32.9**
BeltScale_A04_M5	51.3	58.9	60.1	72.1	100	29.9	43.1	50.8	48.0	71.7	11.4	61.0	45.0	**78.6**	**-29.8**
RDPresent_A04_M1	51.0	32.6	30.3	40.1	29.9	100	53.1	45.2	64.7	46.5	3.6	58.3	39.1	**45.0**	**-49.1**
RDPresent_A04_M2	33.7	61.0	43.7	49.6	43.1	53.1	100	56.5	70.1	46.5	8.8	68.0	43.8	**56.6**	**-54.5**
RDPresent_A04_M3	42.7	43.0	67.5	57.7	50.8	45.2	56.5	100	64.8	68.7	6.9	68.6	60.0	**65.0**	**-47.5**
RDPresent_A04_M4	41.5	44.3	45.8	56.2	48.0	64.7	70.7	64.8	100	68.0	8.9	73.5	48.6	**57.8**	**-60.6**
RDPresent_A04_M5	43.9	49.7	53.7	61.9	71.7	46.5	59.8	68.7	68.0	100	12.6	72.8	55.0	**69.8**	**-49.2**
Ash_Bias	5.9	11.9	1.2	6.1	11.4	3.6	8.8	6.9	8.9	12.6	100	6.8	3.2	**10.3**	**33.9**
RT_Total_Ash	53.7	60.8	59.2	67.6	61.0	58.3	68.0	68.6	73.5	72.8	6.8	100	57.6	**70.5**	**-71.1**
RT_Total_Tons	49.5	38.5	57.7	54.6	45.0	39.1	43.8	60.0	48.6	55.0	3.2	57.6	100	**60.4**	**-34.6**
CCScale	**73.7**	**76.8**	**79.1**	**85.1**	**78.6**	**45.0**	**56.6**	**65.0**	**57.8**	**69.8**	**10.3**	**70.5**	**60.4**	**100**	**-32.6**
Online_Total_Ash	**-25.8**	**-29.7**	**-29.9**	**-32.9**	**-29.8**	**-49.1**	**-54.5**	**-47.5**	**-60.6**	**-49.2**	**33.9**	**-71.1**	**-34.6**	**-32.6**	**100**

6.3 NEURAL NETWORK MODEL

6.3.1 MODEL TRAINING

The back-propagation training algorithm, explained in section 3.3.2.2, is used to train the different NN models. During training, the dataset is split into a dataset containing construction cases and another dataset for validation cases. The model is trained on the construction cases and the validation cases are used to validate how representative the model is of the process.

Three NN models are trained on the online ash measurement and three models on the coking coal mass using the three groups of data. The purpose of choosing three groups is to evaluate the data integrity and model efficiency by comparing the model prediction ability of the three groups of datasets. For the first step in evaluating the data mining algorithms, the model statistics of each model trained on its own dataset[24] are compared in table 20.

Table 20: Groups model statistic comparison

	Group1	Group2	Group3
Stockpile order number	43 – 49	56 – 62	126 – 133
On-line Ash model			
Model fit on Construction cases	85%	72%	85%
Model fit on Validation cases	82%	72%	84%
Overall Model Fit (R^2)	79%	88%	84%
On-line mass model			
Model fit on Construction cases	79%	81%	85%
Model fit on Validation cases	78%	81%	83%
Overall Model Fit (R^2)	80%	69%	79%

Table 20 compares the model fit, as well as the generalisation ability of each model. The model generated on the ash content from all three data groups shows good generalisation since the model fit on the training set is as good as the model fit on the validation set. The same with the model generated on the mass flow of the datasets. These statistics show the accuracy and generalisation of the group models trained on the respective group datasets.

According to table 20, the generalisation ability of the models seem acceptable, however, the model training is still in danger of biased generalisation validation. The validation and construction cases originate from the same process dataset that could

[24] A separate model was trained for each group of stockpiles

limit the simulation of the true dynamics of the system. For a more intensive evaluation on the model accuracy and generalisation ability, the determination of the variance explained (R^2) from each dataset in the different groups using the different models can be evaluated as presented in table 21. The data representing the three groups are introduced to the all three group models. In this way, the danger of biased validation is eliminated.

Table 21: Inter-group model evaluation

		MODEL			
		Group1	**Group2**	**Group3**	
	On-line Ash model				Average
DATASET	**Group1**	79.02%	92.44%	40.87%	**70.78%**
	Group2	66.66%	87.98%	56.74%	**70.46%**
	Group3	53.14%	82.82%	83.60%	**73.19%**
	Average	**66.27%**	**87.75%**	**60.40%**	
	On-line Mass model				Average
DATASET	**Group1**	80.46%	27.30%	58.26%	**42.78%**
	Group2	56.86%	69.14%	61.81%	**62.60%**
	Group3	63.80%	58.08%	78.54%	**66.81%**
	Average	**60.33%**	**51.51%**	**66.20%**	

Evaluating the generalisation extent of each ash content model, the model generated using data from Group2 generalised the best with an average model fit of 87.8% over the three data sets. The Group3 mass flow model generalised the best (66.2%) on all three datasets. The model generated using the Group1 data indicates a model fit of 80.5%. However, the ability of this model to generalise over the other data groups is not as accurate as the Group3 model.

As for the accurate representation of the process dynamicity investigated, the Group2 dataset represents the best. All three ash content models explain an average of 70.5% of the variance in the online ash measurement in the Group1 dataset, whereas the variability of the mass flow in Group3 dataset explains an average of 66.8%. The model fit of the Group2 ash content model, as well as the mass flow model of the Group3 dataset, explains the variance of the ash content and the mass flow the best. Group3 performed the worst.

Visual representation of the model accuracies is the best filter in deciding the most efficient model. Figure 46 tresses the accurate mass flow modelling graphically. This model explains 78.5% of the variance of the actual mass flow. The ability of the mass model to 'follow' the actual mass flow measurements indicates the model capturing the process dynamicity. The mass flow model of Group3, as well as the dataset of the same group will be used for modelling the mass flow in the optimisation step.

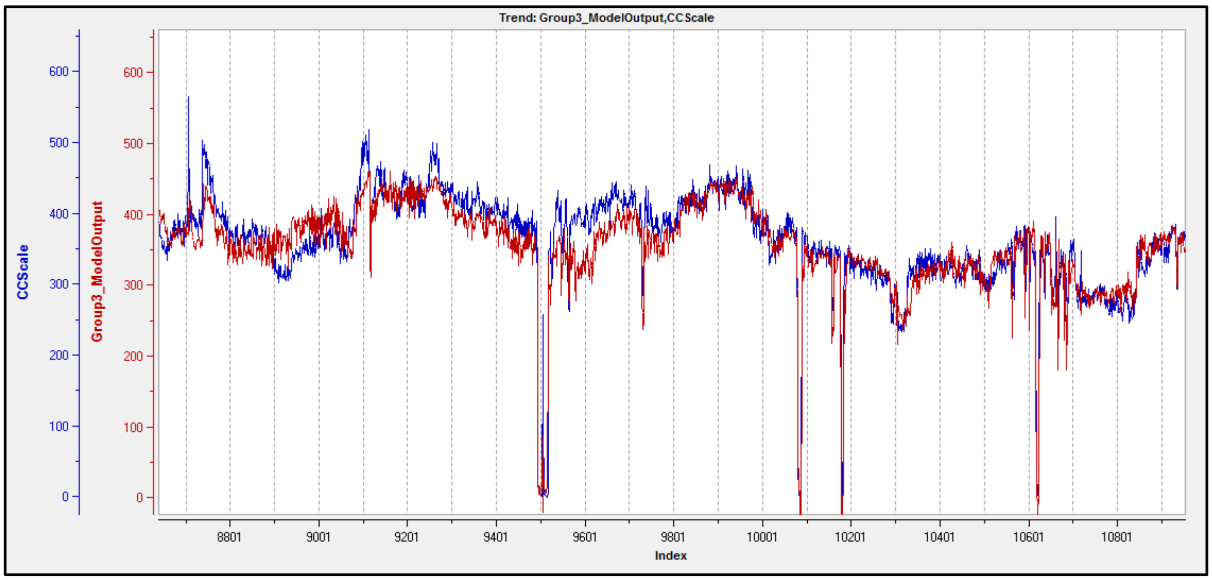

Figure 46: Group3 modelled mass flow vs. actual coking coal mass flow

The accuracy of the mass and ash models could further be quantified determining the standard deviation of the model errors[25] for the specific data group. The standard deviation of the errors between the actual ash content and Group2's modelled ash content is 0.51%. This indicates that the average difference between the actual and estimated ash content is 0.51%. Considering the range in which the ash content is controlled (between 8% and 14%), a 0.51% error could have an unwanted effect on the

[25] A model error is the difference between the actual value and the model value for a specific timestamp.

accuracy of the optimisation. As for the mass flow model generated on the Group3 data, the standard deviation of the errors is 34.7 kg/min. Comparing this average error against the mass flow operating range of 80 kg/min to 500 kg/min, the error will have a negligible influence on the process simulated.

Figure 47 shows the comparison between the actual ash quality measurements and the modelled values generated from Group2 data. Apparent from this graph, the model is able to simulate the dynamics of the process. This is illustrated by the modelled variable 'following' the actual variable. Even though the Group2 model shows the highest generalisation degree in table 21, the objective of this chapter is to identify the most efficient model scenario for further accurate benefit estimation. For this reason, Group2 ash and Group3 mass flow models and datasets will serve as the baseline for the optimisation.

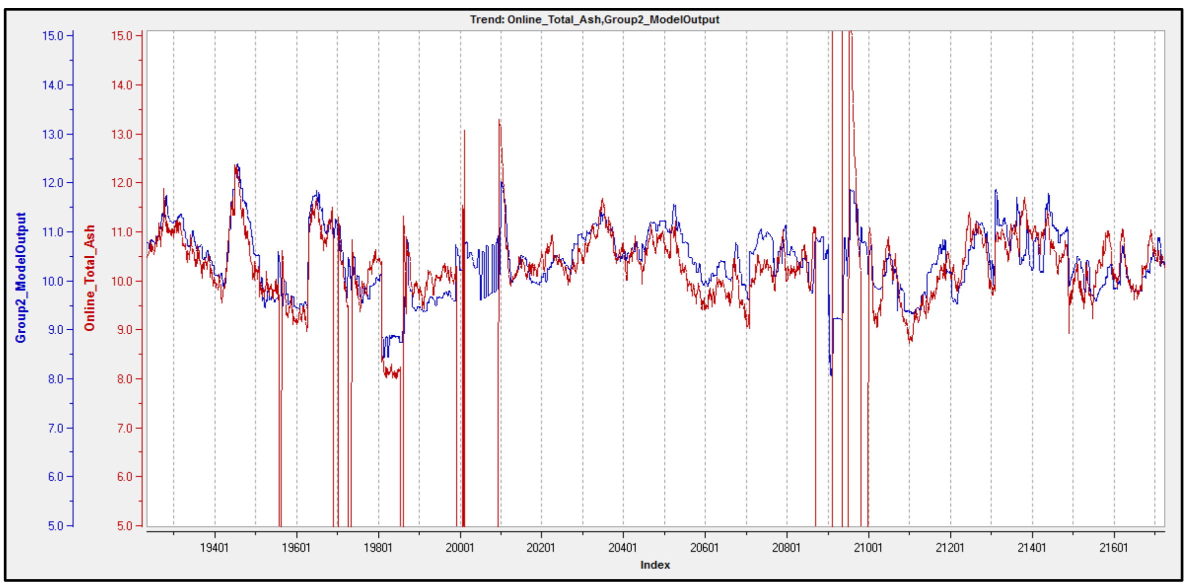

Figure 47: Actual ash content vs. Group2 ash model results

6.4 MODEL DMS VALIDATION

The behaviour of the independent variables in the nonlinear multivariate model will give more insight on the performance of the model. The CSense® wizard providing the environment for nonlinear modelling, include a knowledge extraction platform from where inter-variable relationships described by the NN are illustrated. A comprehensive study on the behaviour of the variables described by the models could lead to the better understanding of the process.

The dense medium RDs per module are the adjustable variables through the adjustment of the RD set points. The correlation between the set points and the actual RD measurements per module are assumed to be at a maximum. This assumption effectively excludes the set point variables from the rest of the analysis. The actual RD variables are classified as the adjustable variables.

Tests were conducted on the influence and the degree of influence the adjustable variables has on the mass model output as well as the ash model output. Several test datasets were introduced to both models in order to generate the necessary model results. These datasets contained the model input variables but the performances of the variables were fixed on the average performance calculated from the raw process data, as discussed in section 5.2. Only the performances of adjustable variables, RDPresent_A04_M1 to RDPresent_A04_M5, were altered in the test datasets. Five datasets were created containing the adjustment of one RD variable while fixing the remaining input variables at their average performance.

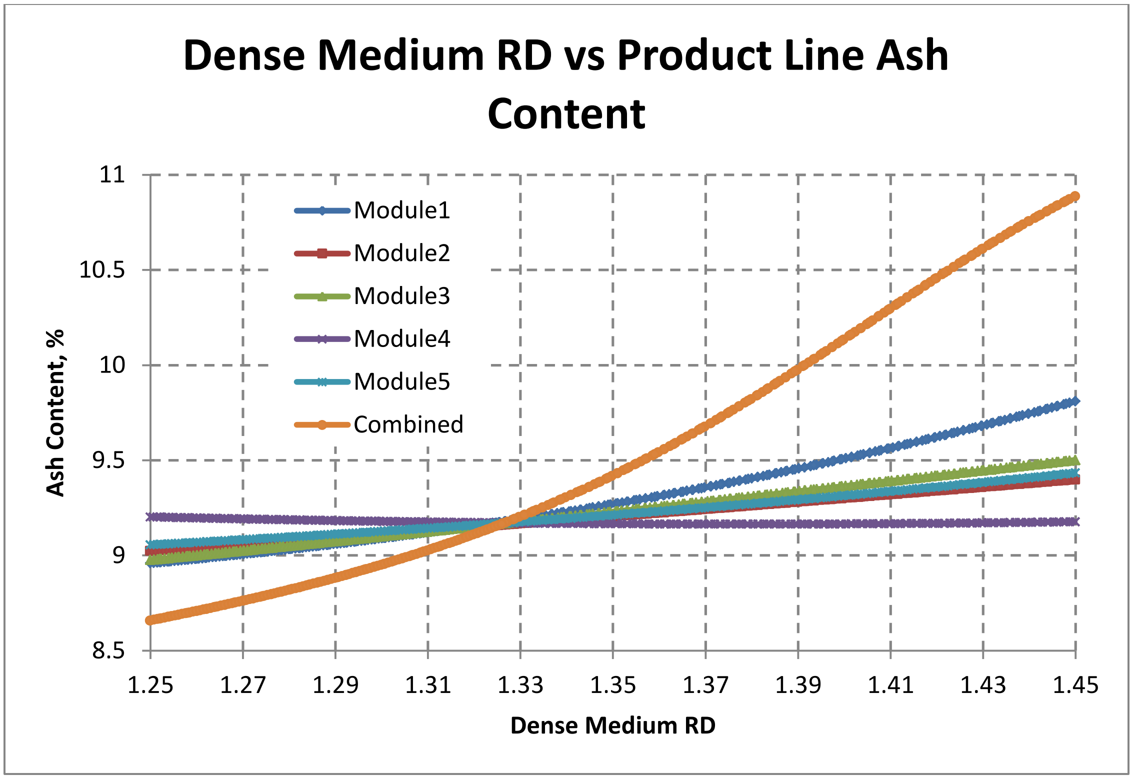

Figure 48: Dense medium RD vs. coking coal ash content

Figure 48 depicts the results produced from the test conducted on the influence each dense medium RD has on the ash content of the coking coal on the product line. Although realistic operation of the coal beneficiation plant at GG1 (as assumed during these tests) will not be realised, these tests give some knowledge of how the model interprets each module's contribution to the plant's operation. An important aspect to realise is that the results generated from the models are based on the combined performance of the five modules. Thus, while adjusting one module's RD values the rest of the modules' performances will have an influence on the outcome of the models.

The performance profiles depicted in figure 48 indicate that the ash content increases with the increase of the separation RDs. The combined ash influence profile represents the influence a combined increase or decrease of all five separation RDs has on the modelled ash content. As mentioned in the literature study, the aiming to control the DMCs to produce the same quality coal is the optimum control strategy. The combined profile illustrates the performance of the process when integrating the optimum control strategy.

As the separation RD in a module DMC increases, more floats are produced with a higher ash content and higher mass.Module1 results show the greatest individual influence on the product ash content ranging between 8.9% and 9.8%. Module 4 shows an indirect correlation between the separation RD and product ash content. This could be attributed to lower average mass flow in that module compared to the other modules. Module4 will have the smallest influence on the coking coal ash content compared to the rest of the modules.

Figure 49 and table 22 illustrates the influence mass has on the ash content on the product line. Consider a cross-section view of the coking coal conveyor belt at GG1 on a particular timestamp. The different sections on the conveyor belt represent the contribution from the floats from each module. Table 22 includes the contribution specifics. Module1's contribution is the largest with 80% of the total mass on the conveyor belt. The ash content of the module1 contribution is 8%. The ash content on the conveyor belt on the specific timestamp is 8.6%. The coking coal ash content is closer to the ash content contribution from module1 then to the other module contributions combined.

This conclusion highlights the importance of controlling the performances of the DMCs to produce the same ash contents. Deviating from this control strategy will complicate the control of the coking coal quality. On the other hand, the feed to the DMCs in the different modules should be constant with equal mass flows, in order to keep the quality control as simple as possible.

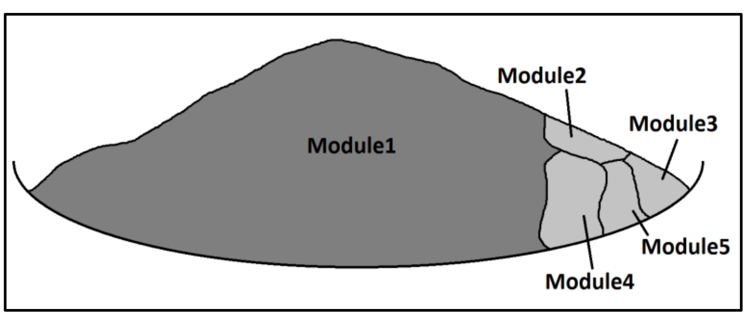

Figure 49: Product line conveyor cross-section

Table 22: Module contribution

Module	Mass Contribution	Ash Content
Module1	80%	8%
Module2	5%	11%
Module3	5%	11%
Module4	5%	11%
Module5	5%	11%

Figure 50 illustrates the nonlinear relationships between the model mass flow output and individual separation RD performances. The ‘combined’ profile illustrates the model’s mass output when increasing and decreasing the separation RD’s of each module simultaneously and to the same degree. The combined performance adopts the optimum coal quality control strategy.

The graphs on both figure 48 and figure 50 have an intercept point at the same separation RD. Each dataset used for the analysis have variables fixed on their individual average performance and one variable that are adjusted. Thus, the intercept point represents the working point where all the input variables are fixed on their average performance.

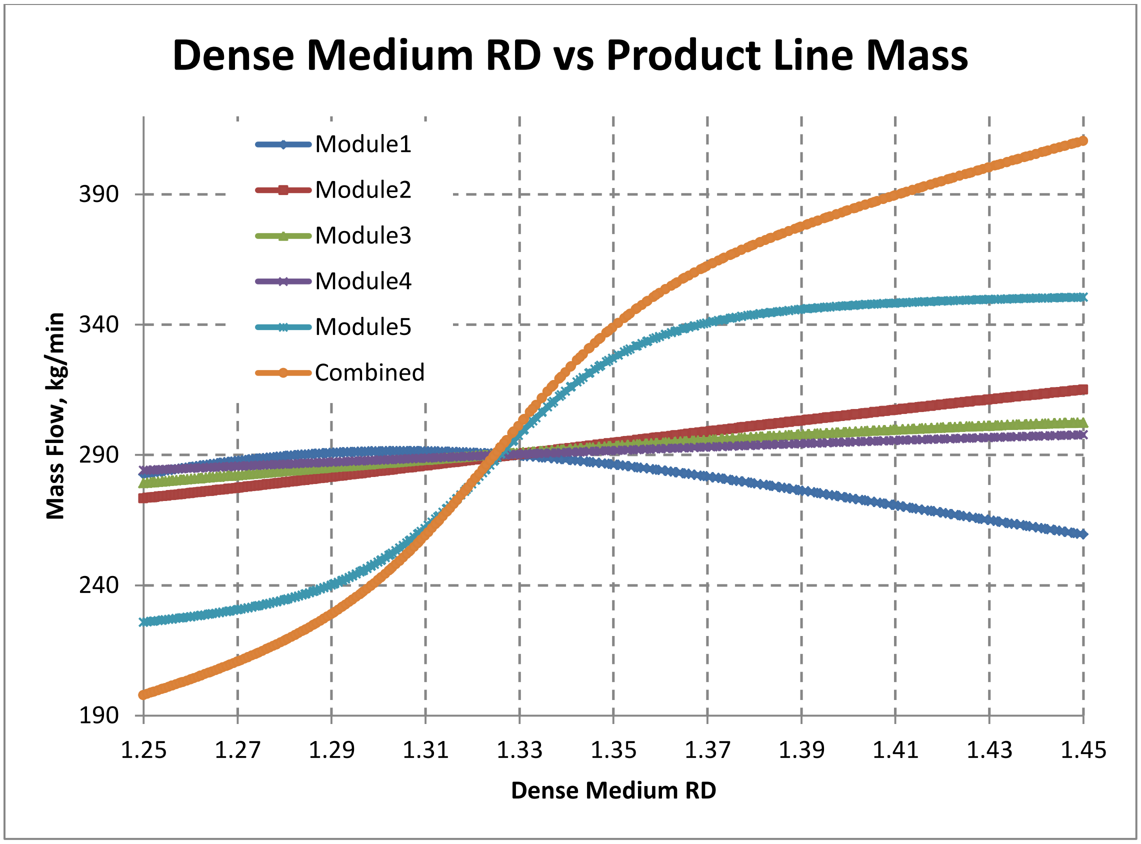

Figure 50: Dense medium RD vs. coking coal mass flow

The ash bias is an indication on how the online ash monitor values compares with laboratory results and to what extent the monitor measures logs inaccurate measurements. The ash bias is included in the input spaces of both NN models. The influence on the performances of both models was evaluated within an ash bias range of between -3.0 and 3.0.

Figure 51 illustrates the influence of the ash bias on the models estimation on the coking coal mass flow. An almost proportion relationship exists between the coking coal mass flow and ash bias. The ash bias could influence the coking coal mass flow with a deviation of approximately 48 kg/min.

Figure 52 illustrates the influence of the ash bias on the coking coal ash content as estimated by the ash model. In contrast to the figure 51, the ash bias has very little influence on the coking coal ash content. The ash content profiles separate at a separation RD of 1.38 and at a separation RD of 1.45 the ash content differs. However, the separation RDs seldom operate at regions above 1.4.

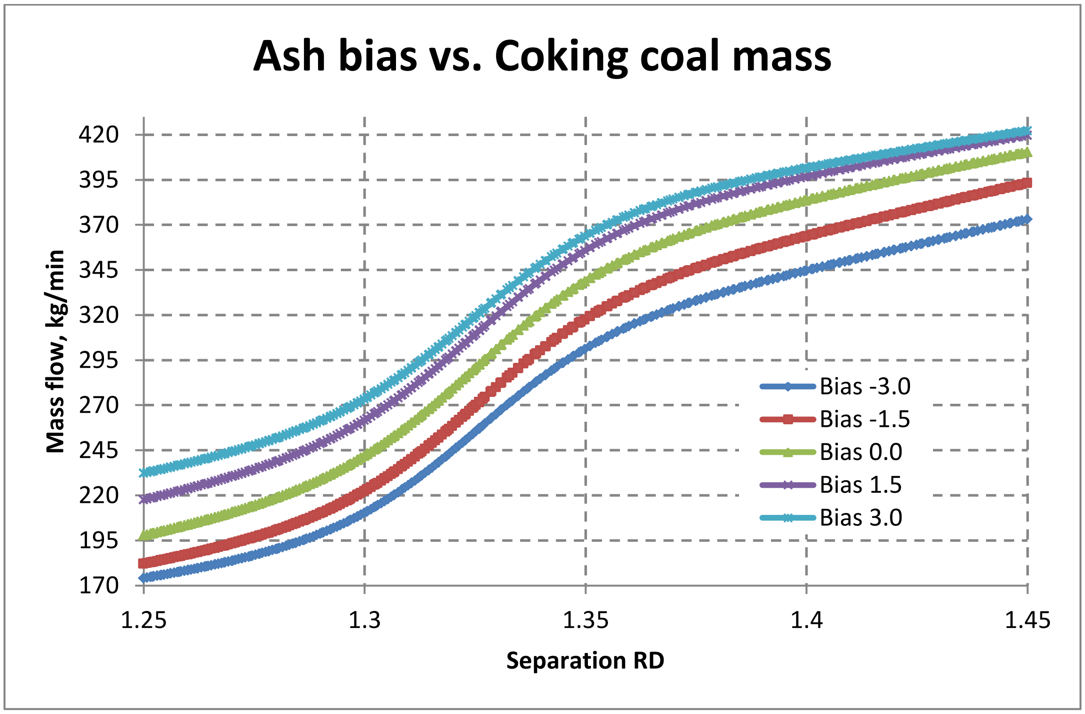

Figure 51: Ash bias vs. coking coal mass flow

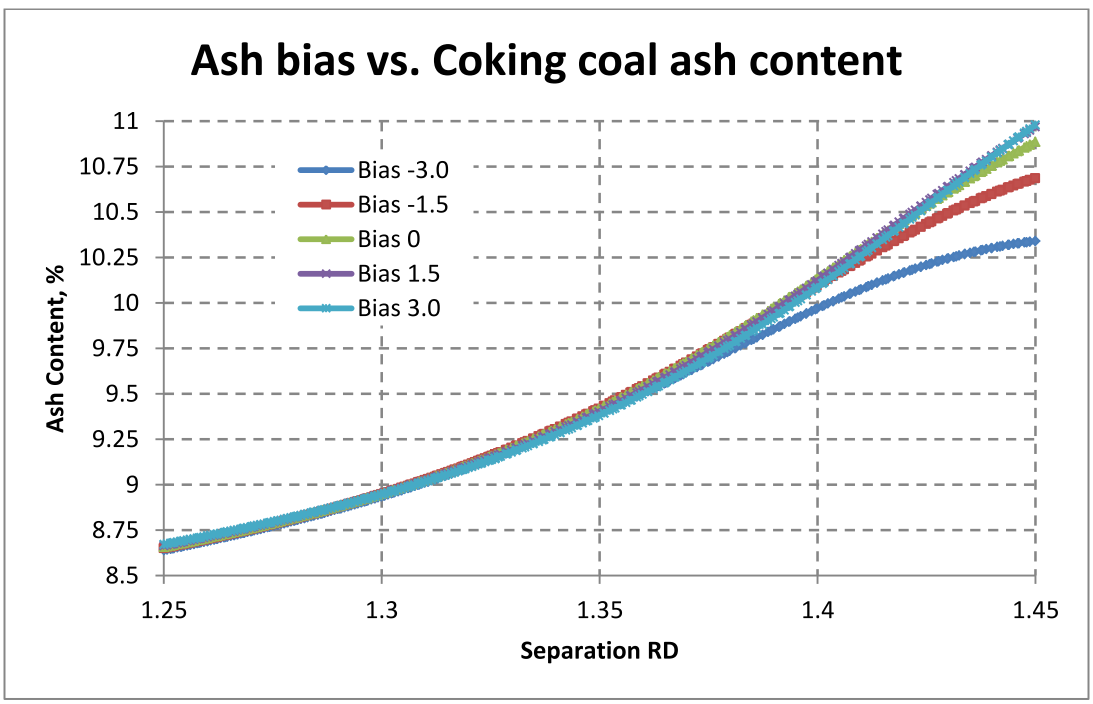

Figure 52: Ash bias vs. coking coal ash content

Because of little information available on the mass balance of the AREA04 coal beneficiation process (as pointed out in section 5.2), the actual coking coal yield of the process cannot be calculated. However, assuming the mass spit on the sieve operations prior to the DMC operations are negligible[26] as well as the influence the spiral product has on the product line, an impression of the yield profile can be recognised.

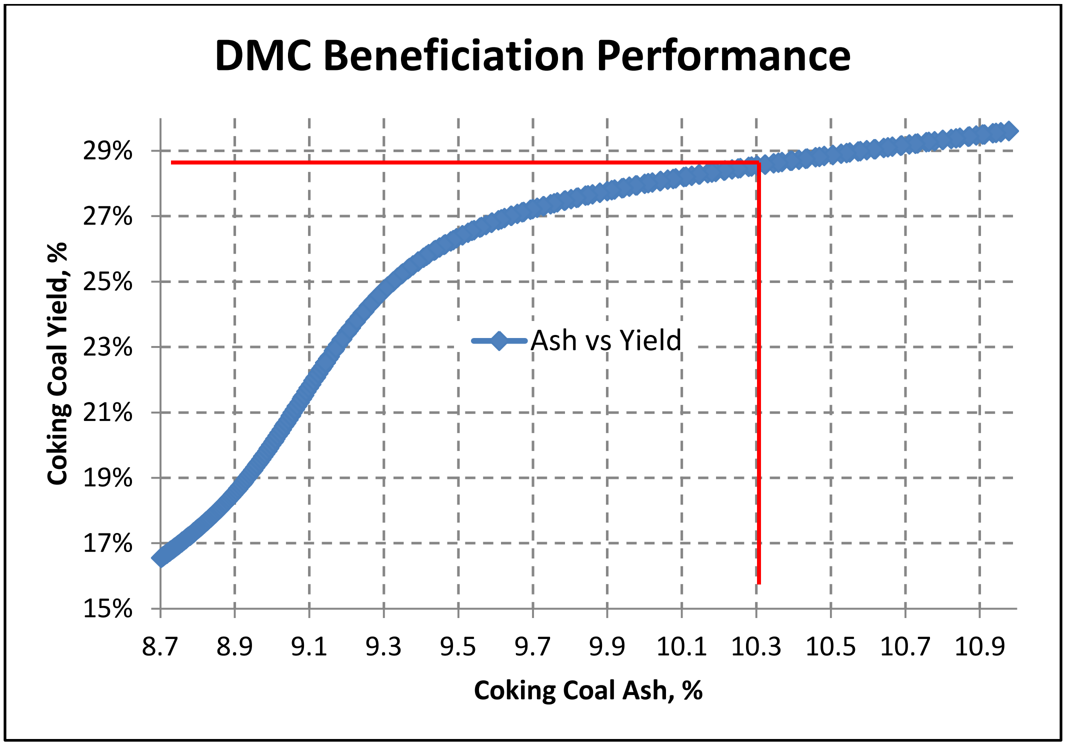

Figure 53: Coking coal production performance

Figure 53 shows the performance on the coking coal production at GG1 as determined by the NN models. The yield was calculated using equation 1 in section 2.3.2. This profile is realistic considering the mass produced by the DMC will increase with the increase of the separation RD and thus the increase in the ash quality produced by the floats. The average ash content target for the stockpiles built at GG1 is 10.3%. As

[26] Negligible mass split refers to 100% of the feed mass flow measured by the belt scales are transferred to the DMC banks.

indicated on the graph, the coking coal yield at this target ash quality should be approximately 28.5%.

6.5 CONCLUSIONS

Two NN models (two hidden layers trained with the supervised back-propagation training method) were generated for each of the three data groups identified in chapter 4. One model used the ash content measured on the coking coal product line as the target variable and the second model used the mass flow of the same product line as target variable. Each model's accuracy and ability to generalise was compared to identify the most accurate model. Data group2's ash model and data group3's mass model were identified as the best models for further investigation.

Inter-variable relationships within each of the chosen models were evaluated. Both models show realistic performance when compared to process knowledge. The complexity of the system lies within the nonlinearity of the input variables to the coking coal mass flow. The ash bias' influence on the system was also evaluated along with the production performance of the coking coal beneficiation process as determined by the NN models.

CHAPTER 7

PROCESS OPTIMISATION

7.1 INTRODUCTION

Results from chapter 6 appointed the model from Group2 as the chosen model for the process optimisation and benefit estimation step. The chosen model explains 88% of the variability in Group2. The model has high generalisation ability and explains an average of 87% of the variance in the three data groups. Group3's mass model was the most accurate with a model fit of 79%. With this model, it is possible to evaluate the outcome on the modelled variables with a single or multiple adjustments on adjustable model inputs. The focus of chapter 7 is to identify the theoretical benefits of these adjustments by optimising the adjustments in such a manner as to meet predefined requirements.

The approach taken in quantifying the theoretical benefits of the optimisation solution is discussed in this chapter 7. The optimisation solution uses the CSense® Architect platform for calculations. This solution compares the calculations from the SBS to the optimised process simulation. For results that are more realistic a sensitivity analysis on process delays and RD operating ranges is discussed in this chapter. The chapter concludes with a discussion of the benefits realised from comparing the optimisation results with SBS results.

7.2 OPTIMISATION APPROACH

The process of estimating the benefits in optimising the quality control on the GG1 coking coal production line requires a specific optimisation solution for reliable results. Several assumptions made over the course of the investigation influences the prospect of deploying the solution at GG1. These assumptions are listed below.

1. The optimisation is done on the RD of the dense medium and not on the set point as determined by operator control. In the optimisation approach, it is assumed that the correlation between the RD set points and the actual separation RD values are at a maximum. This is not the case for online operation. The separation RD values occasionally deviates from the set point.
2. The efficiencies of the sieves upstream from the DMC banks are unknown. Thus, the mass split at the sieves are assumed negligible and the mass flows measured on the belt scales are the same mass flows feeding the DMCs.
3. The operation performance of AREA05 at GG1 is also unknown. A product stream from the spiral classifiers with unknown mass flow and ash content is combined with coking coal product line. The coking coal line from the spiral classifiers will have an influence on the mass flow and the ash content of the final coking coal product line.

Although the solution's objective is to estimate theoretical benefits, the results give a clear understanding and indication to how beneficial the optimisation of the quality control could be.

The goal of the optimisation solution is to optimise the ash quality of the coal around a certain set point through optimally adjusting the relative densities of the dense mediums in the five modules. In optimising the ash quality on the product-line, the cumulative ash quality during stockpile stacking will stabilise. This forms the main objective of this investigation: to identify the degree of stabilisation (if any), as well as the benefit from such a stable and constant ash quality on the product line.

Section 3.4 discusses the operation and application of a GA. Several parameters are required for the desired optimisation performance and outcome. These parameters are mainly the fitness function, the selection method, recombination and mutation factors, the replacement and termination criteria.

The CSense® Architect serves as the platform on which the optimisation solution is developed. This platform allows the simulation of plant operation in real time mode. A data source introduces a dataset to the Architect environment and a data sink is responsible for transferring the results to an external data repository. The data from Group2 will serve as the input set. The ash content model as well as the mass model is included on this platform. An important feature of the CSense® Architect is its ability to integrate the GA with the operation of a NN model and to the necessary calculations in real time. The GA is used to search for the optimum set of separation RDs per module while complying with a certain fitness function. Another important functionality of the CSense® Architect is its ability to feedback new results. With this functionality, the results from the models could be fed back into the solution for the next optimisation execution. In this way, the process at GG1 is simulated.

A constraint to the CSense® Architect is the fact that the parameters to the GA are fixed. As explained in section 4.1, the purpose of the study is investigating a better quality control strategy as well as the benefits of the optimised control strategy (if any). The solution is not a deployable solution since numerous aspects of the optimised control strategy still need further investigation. Table 23 contains the parameters and parameter values for the GA optimisation tool in the CSense® Architect. The parameters are explained in section 3.4.

Table 23: CSense® Architect GA parameters

GA Parameter	Parameter Value
Population size	1000
Number of generations	1000
Mutation probability	0.1
Crossover probability	0.7
Selection strategy	Tournament selection
Termination criteria	Either 1000 generations or when the whole population consists of the same individual

7.2.1 GENETIC ALGORITHM VALIDATION

The fixed parameters of the GA incorporated in the CSense® Architect platform limit the calculation flexibility of this optimisation technique. The parameters described in chapter 3 are not configurable in the CSense® Architect platform. The influence of this limitation needs to be determined.

For a first evaluation, the maximisation of a simple equation is used to validate the output produced by the GA. Consider a multivariate equation given by,

$$z = xe^{-(x^2+y^2)} \ .$$

Equation 19

Using the technical computing software, MATLAB®, a search space is identified to visualise the maxima of the space satisfying the multivariate equation. Figure 54 shows a wireframe parametric surface graph of the equation given above. This functionality of MATLAB® enables the user to view the performance of the dependent variable in a three-dimensional space. The red region builds up to the maximum point for the dependent variable *z.* The EXCEL® global optimisation Solver tool was used to determine the maximum operating point as indicated in figure 54.

Table 24: Multivariable equation parameter optimisation

Parameter	EXCEL Solver	GA
x	0.7071	0.710 ± 0.1%
y	0.0000	0.001 ± 0.1%
z	0.4289	0.430 ± 0.1%

The GA implemented in the CSense® platform was evaluated against the same multivariate function. Table 24 summarises the results from the comparison between the global optimiser and the GA. Because the GA is integrated into a real time platform, the GA was tested for several sequential executions introducing the same parameters. On each execution, the GA produces a new result with an error of ± 0.1% compared to the solver tool results. Although the GA produces very accurate results overall, the fact that the result are not consistent, the GA shows room for improvement.

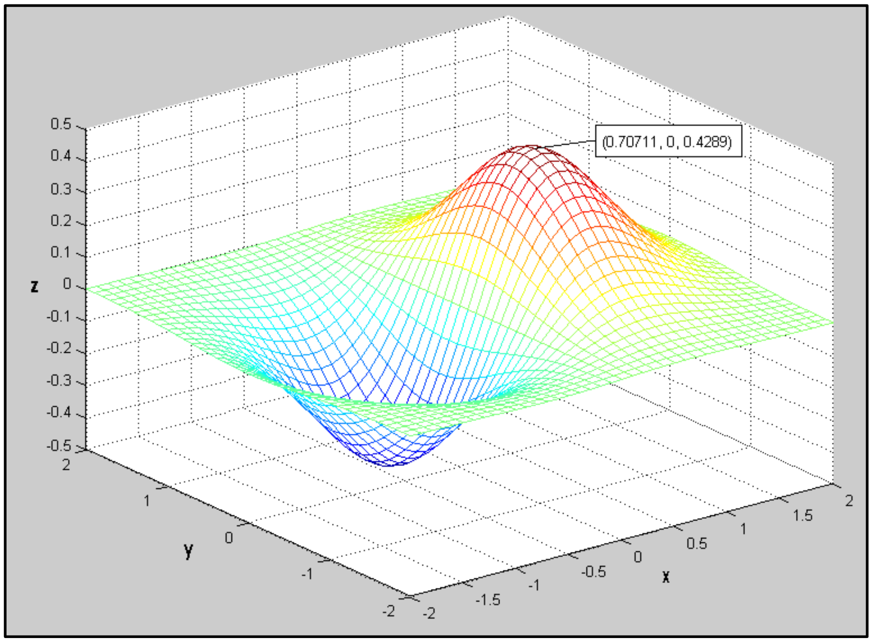

Figure 54: Wireframe parametric surface of a multivariate equation

The coking coal beneficiation process is more complicated than the system tested above. The objective of the second test is to determine how accurate the GA can optimise the modelled ash content compared to a manual search optimisation. For the GA validation on the process under investigation, the state variables were kept at average performance for the first run. This implies that the belt scale measurements, the ash bias and the ash and mass flow measurements calculated in the SBS were fixed on their respective calculated averages. For the second evaluation run, the belt scales values were increased to the average plus one standard deviation (these statistics are available in table 13). In adjusting the state variables, the GA's performance is tested on different process conditions.

The objective of the test is to optimise the modelled ash content adjusting the five separation RDs between 1.3 and 1.4. A comprehensive separation RD search space was created to evaluate as much as possible unique combinations of the five adjustable variables. The input space consisting of the fixed state variables as well as the adjustable variables were introduced to the model to generate an ash content profile over the search space. The error between the ash content target and ash content as model output was logged in order to locate the ash content closest to the target of 10.3%.

Table 25: GA validation results

Parameter	State Variables - Average		State Variables - Standard Deviation	
	Manual Search Minimisation	GA Performance	Manual Search Minimisation	GA Performance
RDPresent_A04_M1	1.3943	1.4000	1.3902	1.4000
RDPresent_A04_M2	1.3891	1.4000	1.3930	1.4000
RDPresent_A04_M3	1.3923	1.4000	1.3959	1.4000
RDPresent_A04_M4	1.3610	1.3000	1.3985	1.3000
RDPresent_A04_M5	1.3987	1.4000	1.4000	1.4000
Mass Flow	379.20	382.79	396.18	397.51
Ash Content Error	0.000354	0.016145 ± 1.0%	0.000137	0.026787 ± 1.0%

Table 25 contains the results and comparisons of the second test. Table 25 shows realistic results when comparing the mass flow optimisation between the two runs. The product line mass flow increases with the increase of the belt scale measurements. The optimisation performance also compares well with the GA showing a slight higher final mass flow. The GA's optimisation results compared to the manual search optimisation is not as accurate. The manual search optimisation was able to locate optimal ash content closer to the target than the GA's optimisation. Figure 55 illustrates the performance of the GA optimising the system with a degree of error compared to the manual search optimisation. Although poorer optimum results are produced by the GA, this optimisation algorithm could still be used to determine the benefits of an optimised control strategy.

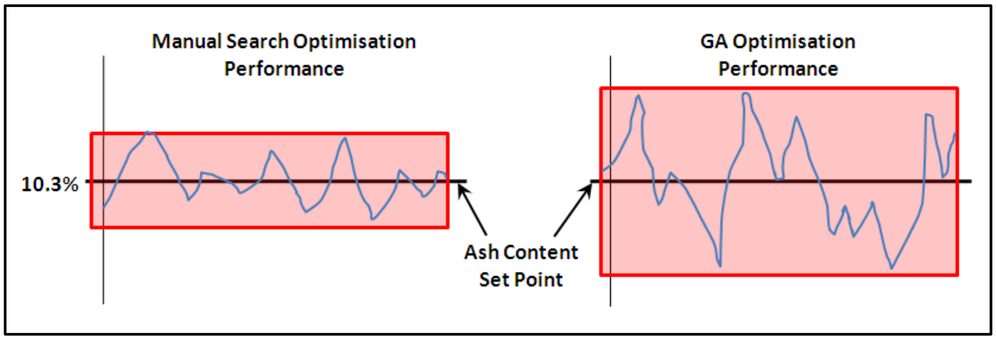

Figure 55: GA optimisation performance

7.2.2 OPTIMISATION SOLUTION ARCHITECTURE

In this investigation, the absolute value of the difference between a target ash of 10.3% and the ash model output is minimised. This minimisation is done through the optimisation of adjustable variables, in this case the relative densities of the dense medium on the five modules (RDPressent_A04_M1 to M5). The RD of the dense medium measurements ranges between 1.25 and 1.45 in each module. However, it is only during offline instances that values of 1.25 and 1.45 are logged. During normal operation, the RD measurements range from 1.3 to 1.4. Thus, the constraints on the GA search space for each adjustable variable are a minimum of 1.3 and a maximum of 1.4.

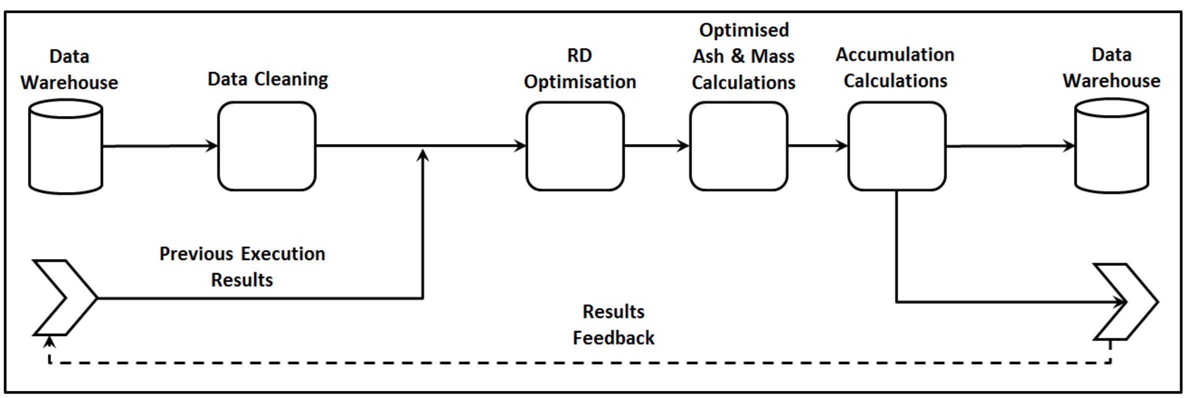

Figure 56: Optimisation solution architecture

Figure 56 illustrates the optimisation solution architecture. Group2 data is introduced into the optimisation environment from the data warehouse. The data cleaning operational block is responsible for the excluding of data outliers. This block classifies into good quality data or bad quality data based on predefined criteria. For this solution, data falling outside of normal behaviour are classified as bad quality data and the solution will exclude the data from further analysis.

The RD optimisation block contains the ash model as well as the GA. The GA search for the optimum RD values for the minimisation of the ash content error. The optimised separation RD values flow to the “Optimised ash and mass calculations” block to calculate the coking coal mass flow using the mass model. The optimised mass and ash content values are transferred to the accumulation block where the stockpile properties for Group2 are calculated on the optimised ash and mass values. The results from the operational blocks are transferred to the data warehouse. A second results stream from the “accumulation calculation” block is fed back to combine with the data fed to the “RD optimisation” block. The feedback loop contains the target ash calculated after each execution. One execution refers to measurements taken on a specific timestamp is fed to the solution, calculations are performed and results are generated.

The SBS assists the quality control operator in adjusting the set points of the RDs on the magnetite recovery system. This assistance comes in the form of a target ash parameter that indicates the ash percentage needed in order to keep the average ash content on the stockpile in the region of 10.3%. If the cumulative ash rises above the set point, the target ash will return a value lower than the set point. This target ash logic is implemented into the optimisation solution. A target ash is calculated at the end of the solution execution and the value is fed back to the GA for the minimisation of the cost function. In this way, the logic behind the SBS is simulated and optimised in the solution. The dynamic ash target approach is more efficient than using the fixed ash content set point of 10.3% for the cost function minimisation. The logic is included in the solution by means of a script in the “accumulation calculations” block. The logic script is available in appendix C.

The optimisation solution determines the optimum ash and mass flow values from the models generated in the data mining stage. The optimised separation RD values, as well as the model inputs corresponding to the model training inputs, are introduced to the respective models to generate the optimum ash and mass flow values.

The SBS determines the accumulation of the ash content on an active stockpile sequentially based on a weighted average calculation. This same principal was implemented into the blueprint solution in the "accumulation calculations" block, calculating the accumulation of the average ash content, as well as the stockpile mass accumulation. This layer of the solution also ignores the instances where the online ash analyser and/or the belt scale measuring the mass flow on the coking coal line were offline.

All the original fields introduced to the solution from the SQL warehouse, as well as the newly calculated fields are logged in a text file compatible to several data reading programs. The logged data will enable further optimisation evaluation and benefit estimation.

7.2.3 OPTIMISATION EVALUATION

To evaluate the efficiency of the optimisation, the results need to be compared to ideal outcomes. An effective and simple approach in testing the optimisation accuracy is to plot the optimised target value to the actual target measurements in a scatter plot. Three possible scatter plot outcomes are illustrated in figure 57. Plot (a) depicts incorrect influence of the optimisation on the target variable. This plot clearly indicates that optimisation occurred on the target variable but the cost function was not minimised around the target ash set point. In case of poor optimisation influence, the optimised ash values have a high correlation to the actual ash measurements generating a graph illustrated in plot (b). Low actual values correspond to low optimised values and high values correspond to high-optimised values. Plot (c) illustrates an ideal optimisation outcome. The actual ash values are optimised around the set point. Results as described in plot (c) show a more stable quality control on the coking coal ash content. This analysis will be referred to as the aggregation evaluation in the rest of the paper.

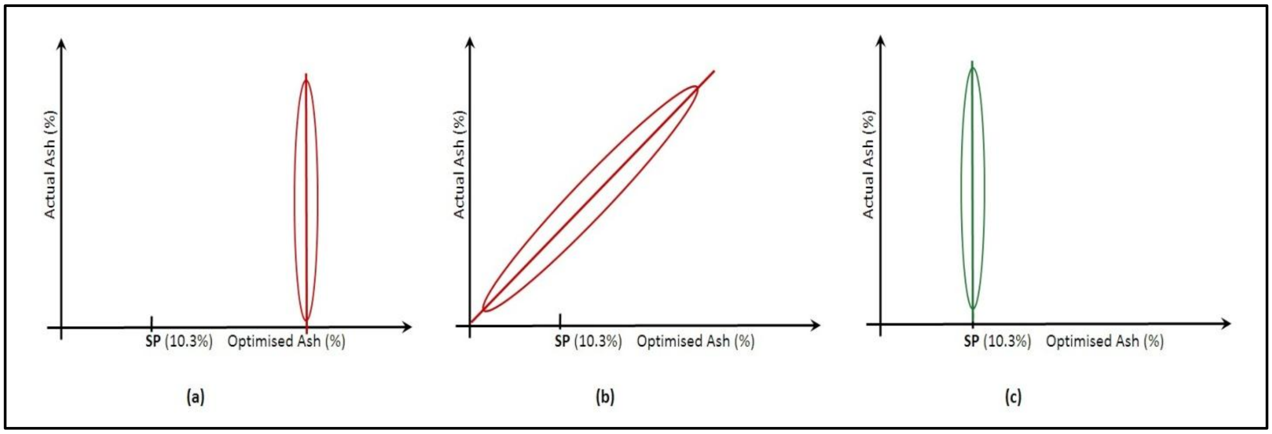

Figure 57: Optimisation evaluation from scatter plot analysis

Figure 58 shows one optimisation run[27] at an execution rate[28] of 8 seconds. The optimised data falling within a certain region between 10.0% and 10.6% around the set point (depicted by the green line), is regarded as good optimised data. The data falling outside of this region are considered as poor optimised data. The optimisation result as presented in figure 58 are indicative of good optimisation during the first optimisation run as the plot takes on the form of plot (c) in figure 57. 84% of the optimised values aggregate around the set point (between 10% and 10.6% ash content). The remaining 16% of the poorly optimised values fall outside of the range, either due to the execution rate constraint or due to the inaccuracy of the model.

[27]Optimisation run refers to one execution cycle of the entire dataset through the solution.
[28]The execution rate of the solution is the time from one data record execution to the next data record execution.

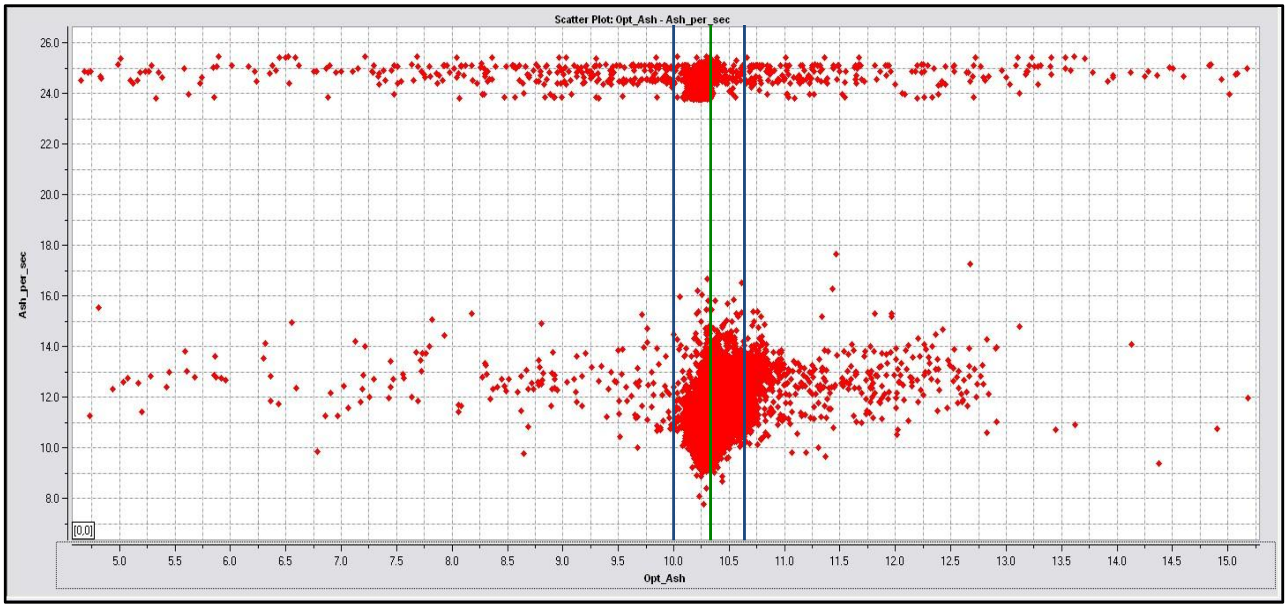

Figure 58: Optimisation evaluation scatter plot (Actual ash vs. Optimised ash)

Optimisation efficiency is subjected to several constraints and parameters. One of the constraints is a solution hardware constraint. During optimisation, the nonlinear optimisation operator calculates the optimum RD values for a minimum cost function. This process of absolute minimum identification takes time and absorbs computer memory. As mentioned in chapter 3, the computational intensity of a GA is one of its drawbacks. If the execution rate is too short, the nonlinear optimisation will not be able to determine the minimum and the data point will not reach closest possible value to the set point. Setting the execution rate too long, the time the solution needs to execute all the records in the dataset will be too long. However, a data record not reaching the predefined set point may also be due to the inaccuracy of the GA.

The next step is to complete several optimisation runs at different execution rates to determine at what point model inaccuracy contribute to poorly optimised records. For this sensitivity analysis, three optimisation runs were executed at different execution rates. Figure 59 represents the results from the optimisation runs at different execution rates.

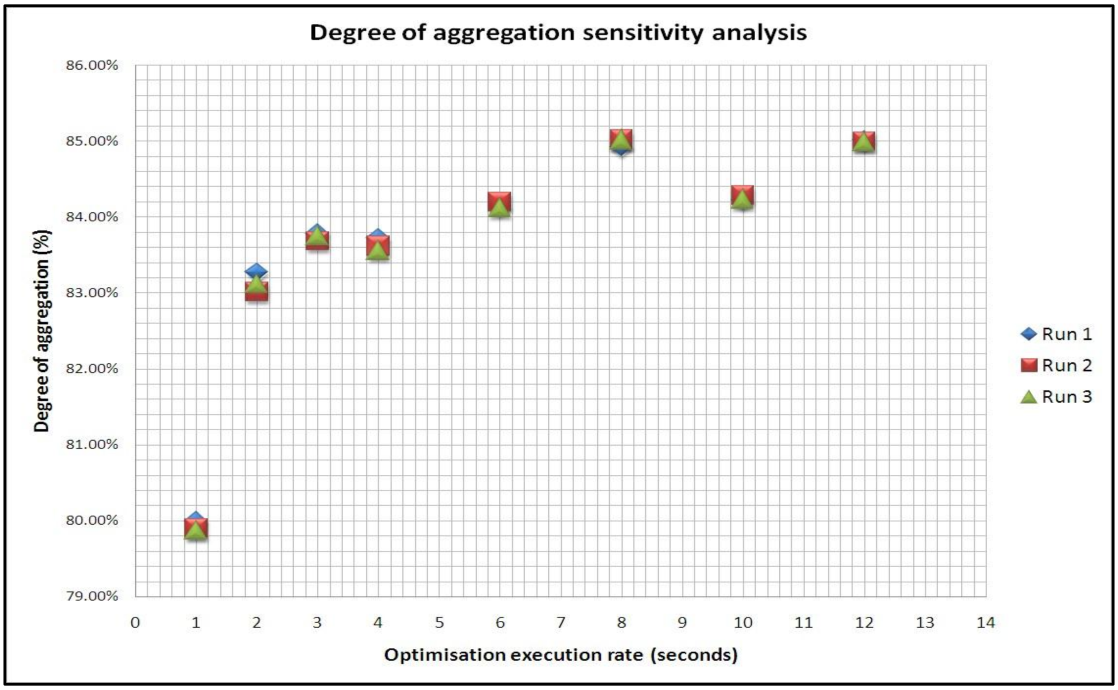

Figure 59: Sensitivity on the degree of data aggregation

For an execution rate of 1 second, an average of 79.92% of the data from the three runs falls within the good optimisation region. Apparent from the graph, the degree of aggregation flattens out at 6 seconds. In other words, at this point model inaccuracy is the greater contributor to the optimised data falling outside of the good optimised data region. Another observation is the reliability of the optimisation solution, as the results from the different optimisation runs are consequent. A fixed execution rate of 8 seconds was chosen from the remainder of the optimisation runs. This implicates that on average 15.02% of the optimised results at an execution rate of 8 seconds are defined as poorly optimised data.

As mentioned in chapter 3, a GA is not often implemented as an online application. The reason for this is the GA being computational intensive. With the analysis results depicted figure 59, the GA is able to reach convergence on within 6 seconds. Because the sampling rate of the solution is one minute, the solution could easily provide the operator with the optimised separation RD values before the next execution after one minute. This property enables the implementation of a GA optimisation solution on the GG1 quality control system.

7.3 BENEFIT ESTIMATION DISCUSSION

The focus of the investigation is to assess the feasibility of an optimised quality control on a coking coal production line. The investigation is a theoretical introduction to the optimised control strategy concept. To explore the success of the investigation, the results from previous stages of KD should be evaluated. This section is dedicated to discussing the results and possible benefits from the optimisation results.

7.3.1 ACTUAL VS OPTIMISED DATA ASSESSMENT

7.3.1.1 ONLINE ASH MEASUREMENTS VSOPTIMISED ASH CONTENT

As explained in the solution architecture section, the cost function of the ash quality was minimised, optimising the dense medium RD values. The aim of the solution was to optimise the ash quality around the set point of 10.3%. Figure 60, figure 61 and figure 62 stress the success of the optimisation. As illustrated in the ash quality trend, the actual ash was controlled around the set point but with significant fluctuations, while the optimised ash remained relatively stable on the set point. This stable control of ash quality indicates less good quality coking coal is lost to Matimba Power Station or, on the other hand, bad quality coal sent to the coking coal stockpile. The light grey areas on the graph indicate periods where the process was offline. Figure 60 shows performance of the optimised ash versus the actual ash.

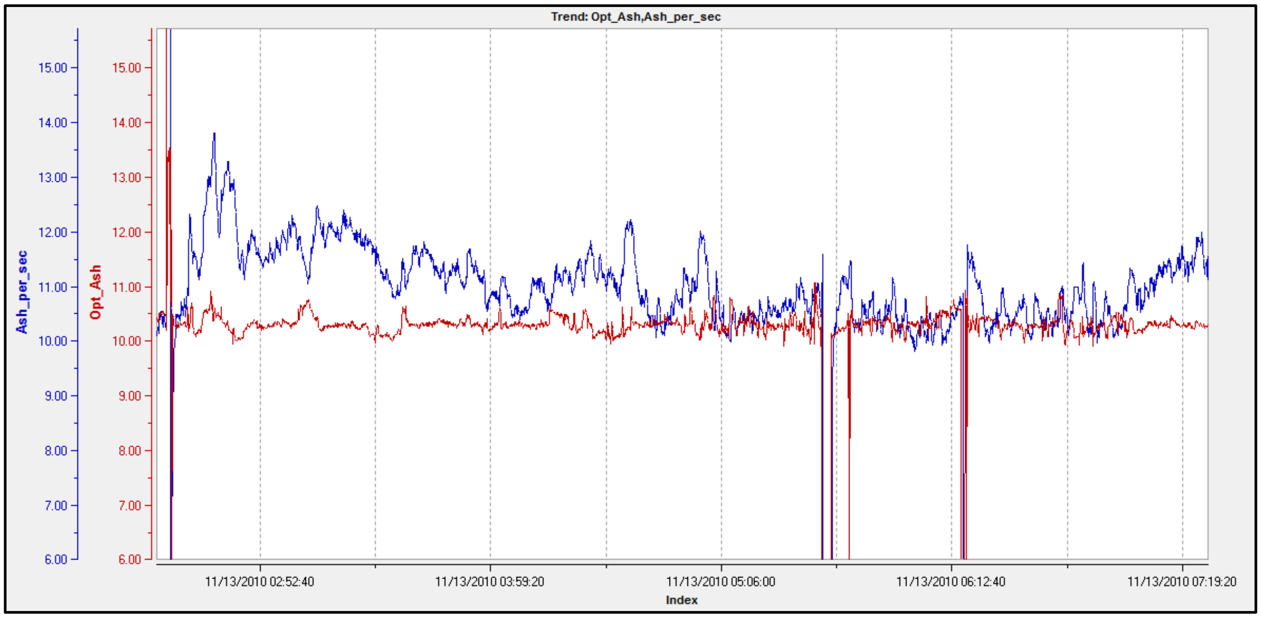

Figure 60: Actual ash readings vs. optimised ash results

Figure 61 represents the distribution of the actual ash measurements from the online ash analyser. This distribution is widespread and not as concentrated around the set point as figure 62. The distribution for the optimised ash field shows a clear concentration of values around the set point. The objective defined in section 1.1 is achieved with these results. The variance of the controlled variable is smaller around the defined set point of 10.3% ash content.

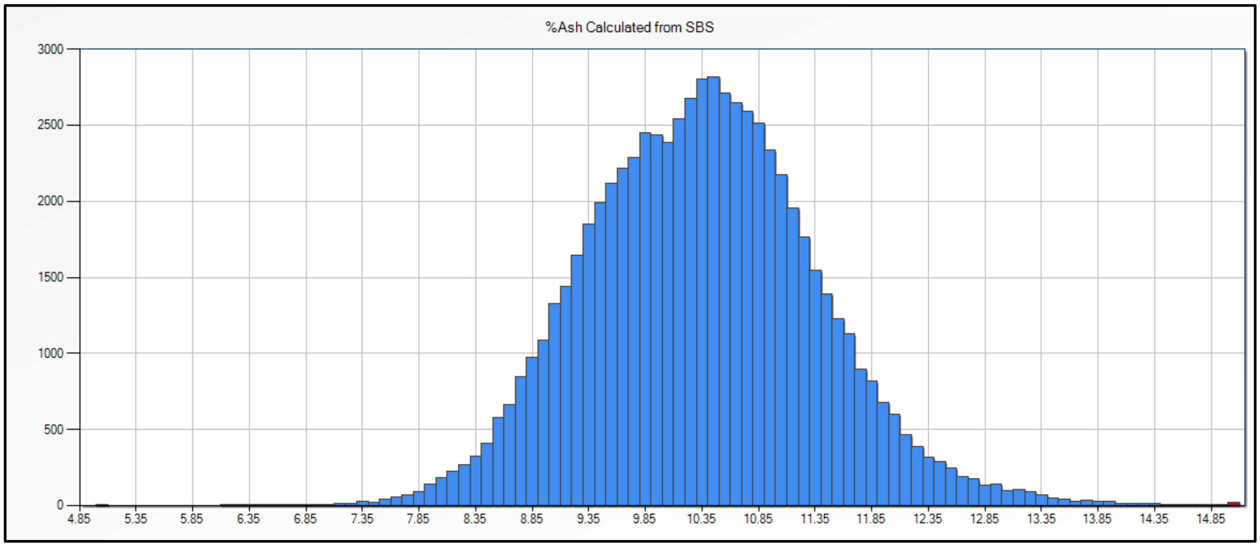

Figure 61: Histogram of actual ash readings

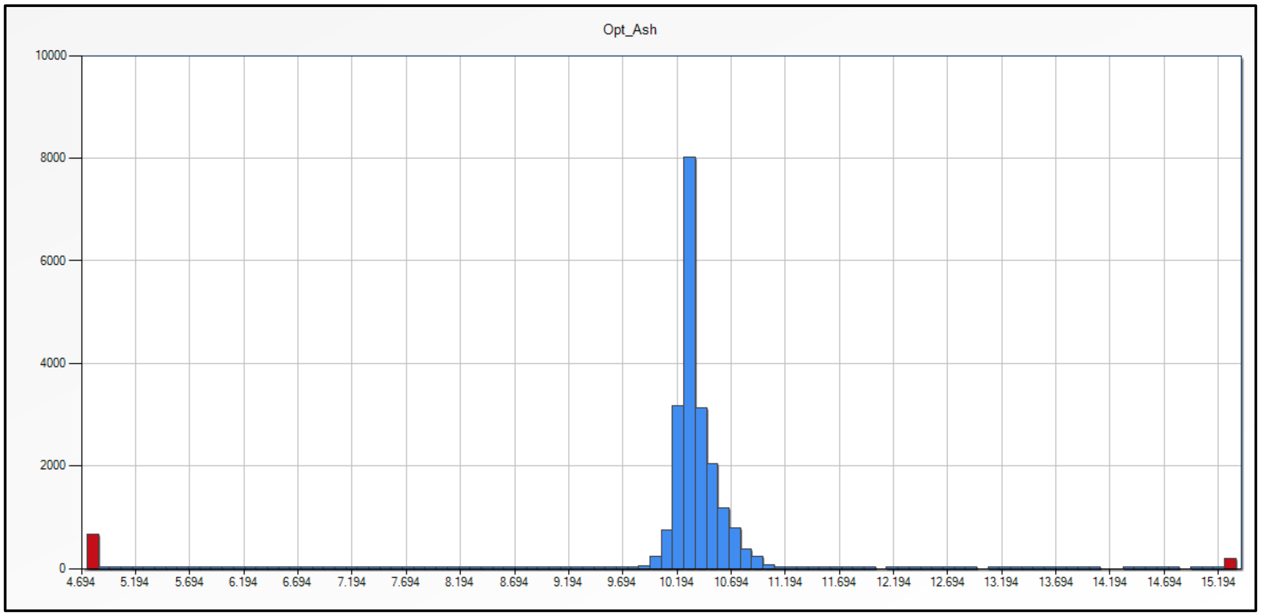

Figure 62: Histogram of optimised ash distribution

Rigorous and rapid changes in the dense medium RD on the five modules were necessary for the optimisation success on the stable ash quality. The actual execution rate if simulated in real time is one minute. For every execution of a data record in the solution blueprint, the RD's were optimised. Thus, for the optimised results, every minute a fictitious RD change occurred ranging from 1.3 to 1.4. The magnetite recovery system will not be able to comply with such an aggressive control. Figure 63 and figure 64 illustrate the rigorous and rapid RD changes during the optimisation on the RD source measurement on Module1. Figure 64 shows the equal distribution of RD values across the distribution histogram, except for instance where the production line was offline.

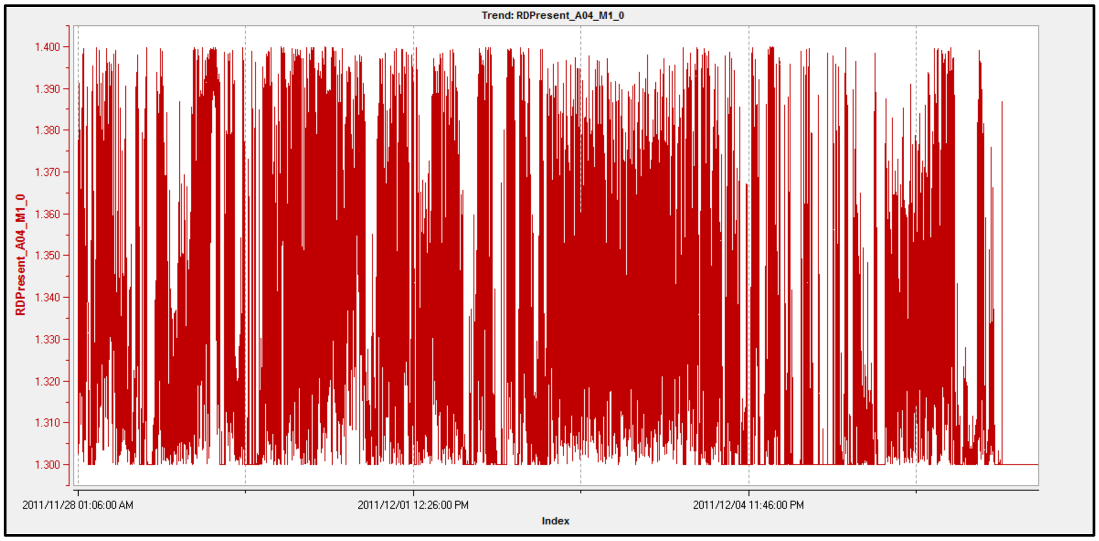

Figure 63: Optimised RD trend for RDPresent_A04_M1

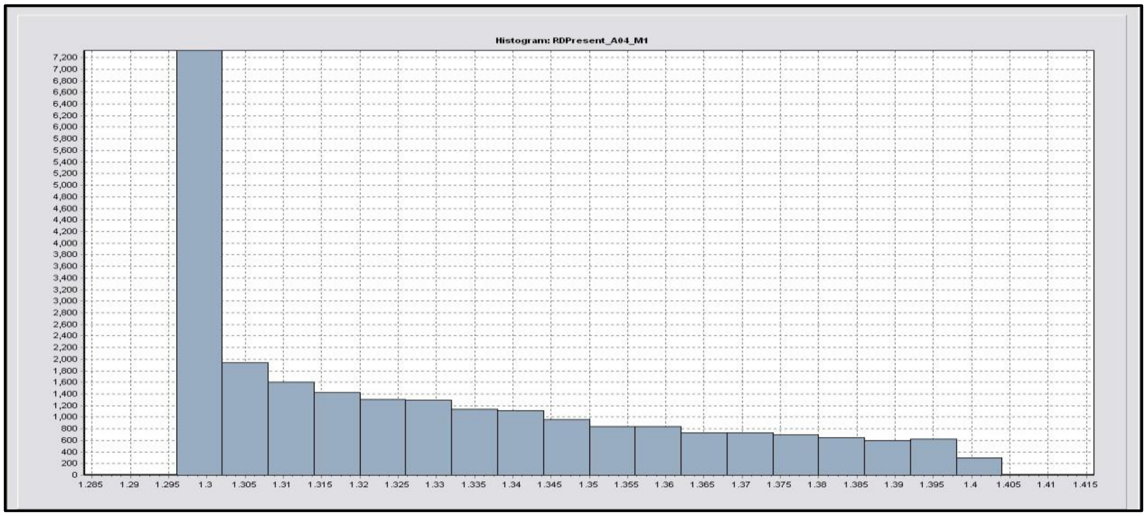

Figure 64: Optimised RD distribution for RDPresent_A04_M1

If this solution were to be implemented in GG1, the control of the dense medium RDs would have been too strenuous to the control loop managing the magnetite recovery system. The high controller reversals would have caused repeated maintenance on the process units. In addition, the time delay from a RD set point change to viewing the effect on the dense medium RD is longer than one minute (depending on an increase or decrease and the degree of set point change).

7.3.1.2 STOCKPILE ANALYSIS

Stacking a coking coal stockpile with a constant coal quality is the focus of this investigation. Fluctuations across the set point of 10.3% ash content lead to the loss of quality coal as explained, regardless of the final ash content average reaching 10.3%. The set point, as well as the cumulative ash and optimised cumulative ash quality is trended per stockpile on the multi-trend graph in figure 65. The actual ash accumulation (red) progression shows much more fluctuations than the optimised accumulation (blue) progression.

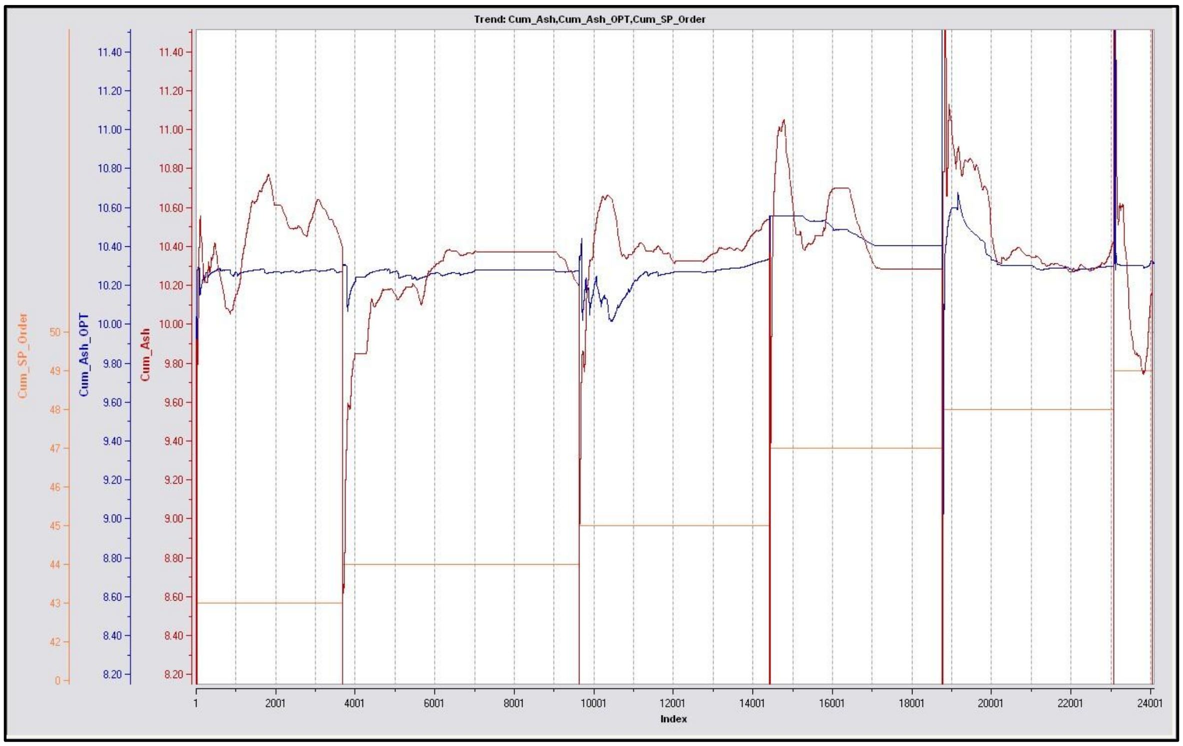

Figure 65: Cumulative ash vs. Optimised cumulative ash per stockpile

Figure 66 compares the actual and optimised ash accumulation on each stockpile. Comparing the average ash stacked on each stockpile in the optimised and actual calculations, five of the seven optimised stockpiles average closer to 10.3%. Stockpile 46 may be exempted because of the low accumulated mass of the stockpile. As for stockpile 47, the target accumulated mass for the specific stockpile was 27 000 tons. GG1 only stacked 60% of the intended mass accumulation. The calculated target ash values (used in the nonlinear optimisation operation cost function and responsible for the set point of the manual control) were not aggressive enough to force the cumulated ash to 10.3% in time.

Table 26 provides a comparison summary of the measured properties for each stockpile. The average absolute error from the set point to the operation point for each stockpile is also included in this summary. The stability of the optimised ash accumulation is apparent from this absolute error summary. An assessment on the mass accumulation is included in the final section of this chapter.

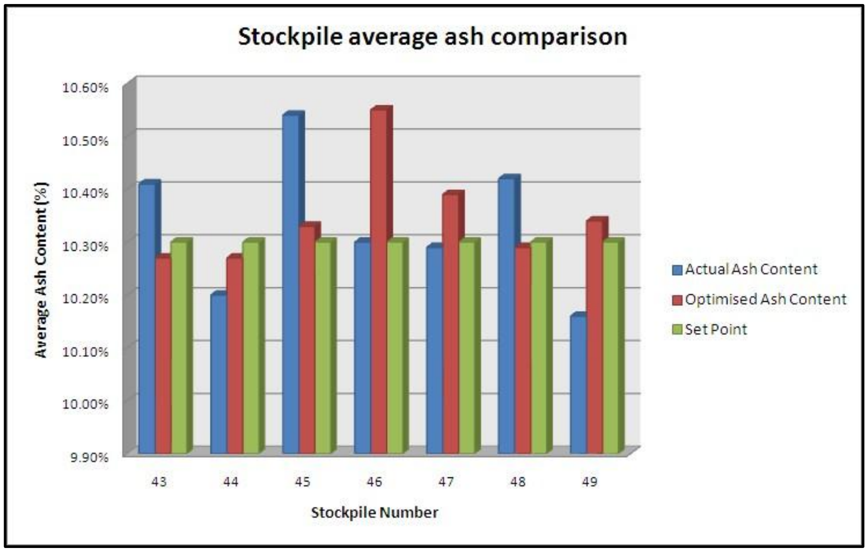

Figure 66: Stockpile average ash comparison

Table 26: Comparison of stockpile properties

Stockpile Name	**Stockpile Number**	**Average Ash** Actual	**Optimised**	**Absolute Error** Actual	**Optimised**
Group 1	**11/19/2007 21:40:00 to 12/6/2007 15:00:00**				
2K02692	43	10.41	**10.27**	0.237	**0.030**
1K02693	44	10.20	**10.27**	0.156	**0.050**
2K02694	45	10.54	**10.33**	0.140	**0.098**
3K0695	46	10.30	**10.55**	4.157	**1.259**
3K02695	47	10.29	**10.39**	0.195	**0.163**
4K02696	48	10.42	**10.29**	0.208	**0.088**
NK02697	49	10.16	**10.34**	0.497	**0.0129**

7.3.2 SENSITIVITY ANALYSIS

Sensitivity analysis studies were conducted on the operation range of the separation densities in the five modules, process time lags, as well as the delay on separation density adjustments. These studies increase the knowledge into the extent of potential improvement. The results from this section provide direction for intelligent process development, identifying what aspects of the process influence performance of the process the most. Stockpiles 43 (2K02692), 44 (1K02693), and 45 (2K02694) are the stockpiles under investigation in this sensitivity analysis section.

7.3.2.1 RD RANGE SENSITIVITY ANALYSIS

As mentioned in the previous section, the optimisation of the RD sources values result in rigorous adjustments of the separation density. In practice, this control with these rapid and large changes is not realistic. A sensitivity analysis was conducted to investigate the influence the RD operation range had on the ash quality control. The RD ranges were decreased for every optimisation run. For the first run, the RD optimisation range was set from 1.3 to 1.4. The second run minimised the cost function by optimising the RD values within a range from 1.31 to 1.39. The same principle counted for the third and fourth run. For the last run (fourth run), the optimisation ranges were fixed from 1.33 to 1.37.

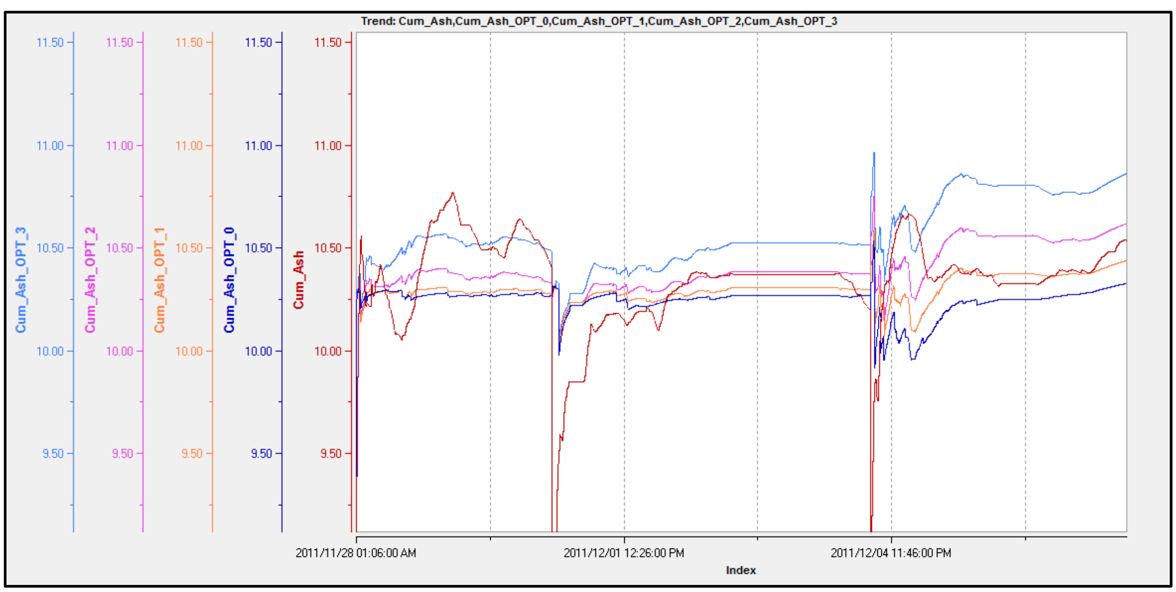

Figure 67: Ash accumulation on stockpiles for different RD optimisation ranges

The ash quality accumulation on stockpiles 43 to 45 for the different RD ranges shows the greater offset for smaller RD ranges as illustrated in figure 67. The first and second optimisation runs were more accurate than the actual stockpile quality for the three stockpile builds. The third and fourth optimisation runs were inaccurate for the three stockpile builds. The ash accumulation progress also shows signs of higher fluctuation at smaller RD operation ranges.

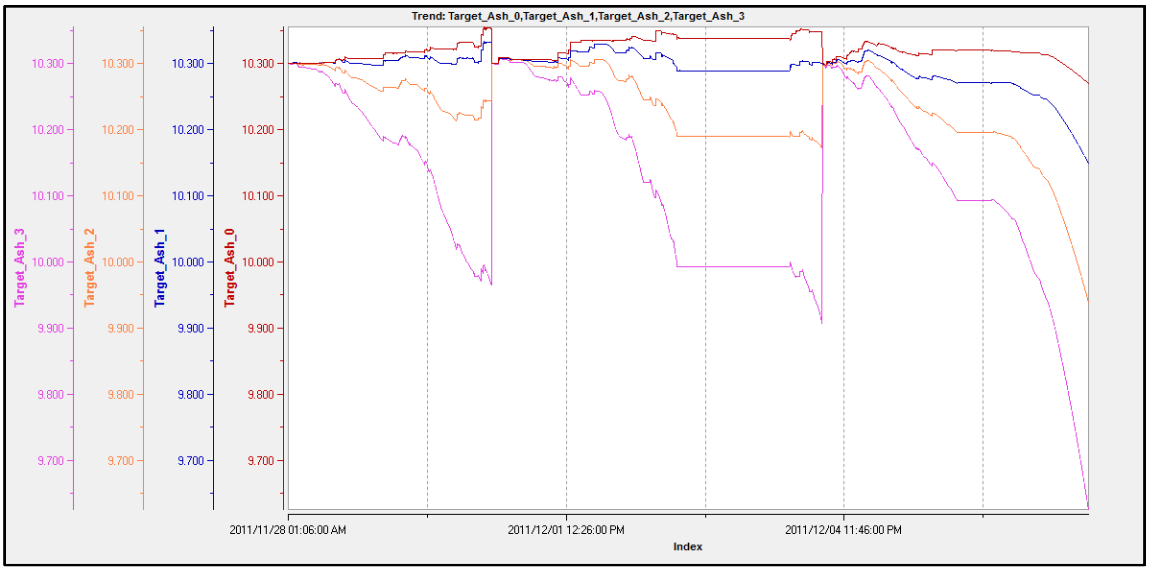

Figure 68: Calculated target ash for RD ranges sensitivity analysis

The aim of the optimisation is keeping a stable ash quality production, as well as produce stockpiles with an average ash content of 10.3%. As mentioned in the previous section, the cost function used for the minimisation contains a calculated target ash value. This calculated ash target indicates what the ash quality production should be in order to stack the current stockpile with an average ash content of 10.3% for the specified mass target. Figure 68 shows the target ash profiles of each of the four optimisation runs. Evident from this multiple trend, the performance of the RD control decreases exponentially with decreasing RD operation range. Lower target values indicate a higher demand for better quality coal with lower ash content. Coal with lower ash content is scarcer than poorer quality ash.

The optimisation results from optimisation run 4 (RD ranges 1.33 to 1.37) are explained in figure 69. The operation profile of a RD variable from run 1 (red) and run 4 (pink) clearly emphasises the cause for poor performance. The grey regions in figure 69 indicate regions of normal operation on the ash content production (blue). In these regions, the optimisation is increasingly restricted to the RD range limits as the RD ranges decreases. For the complete minimisation of the cost function the RD value (in the case of figure 69, RDPresent_A04_M1) should be adjusted to values beyond the RD range limit of 1.33. For this reason the RD values from run 4 show constant values on the range limits and thus causes poor quality control.

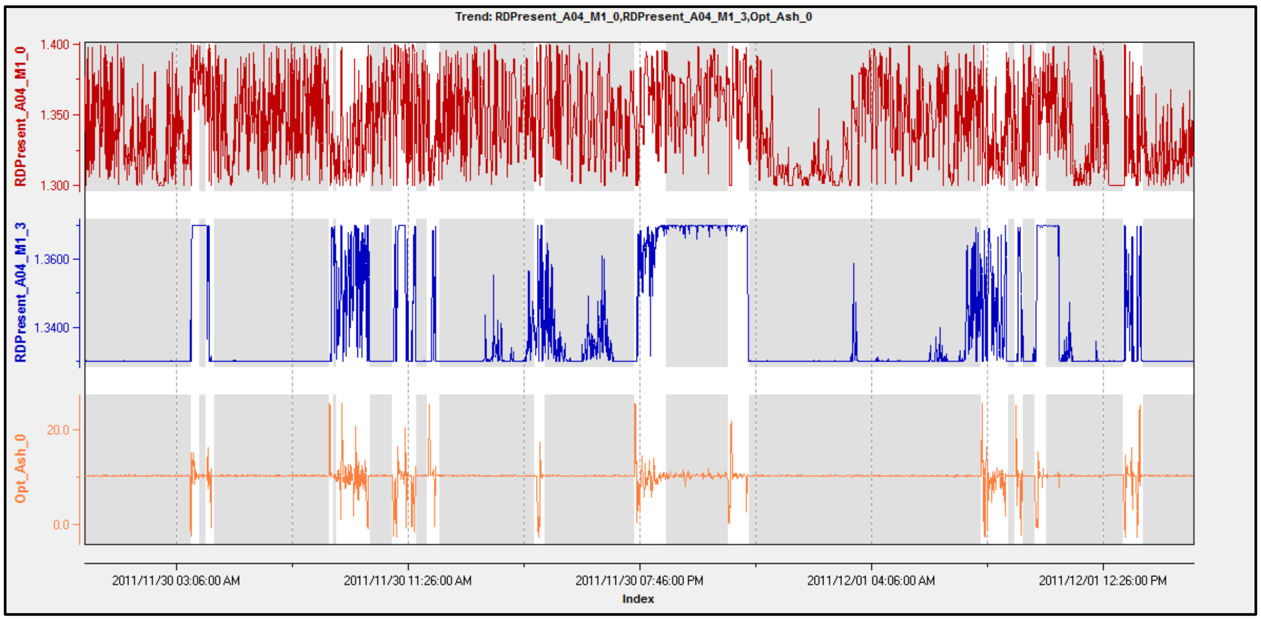

Figure 69: RD performance comparison for four optimisation runs

The set point aggregation bar chart shows the influence the RD optimisation range has on the accuracy of the ash quality optimisation. The accuracy of each optimisation run is compared in figure 70 using the principle of set point aggregation. The smaller the RD operation ranges (equal quantity subtracted from the upper and the lower optimisation limits), the less accurate the minimisation around the set point becomes. The aggregation bar chart sums up the influence the RD range has on the optimisation.

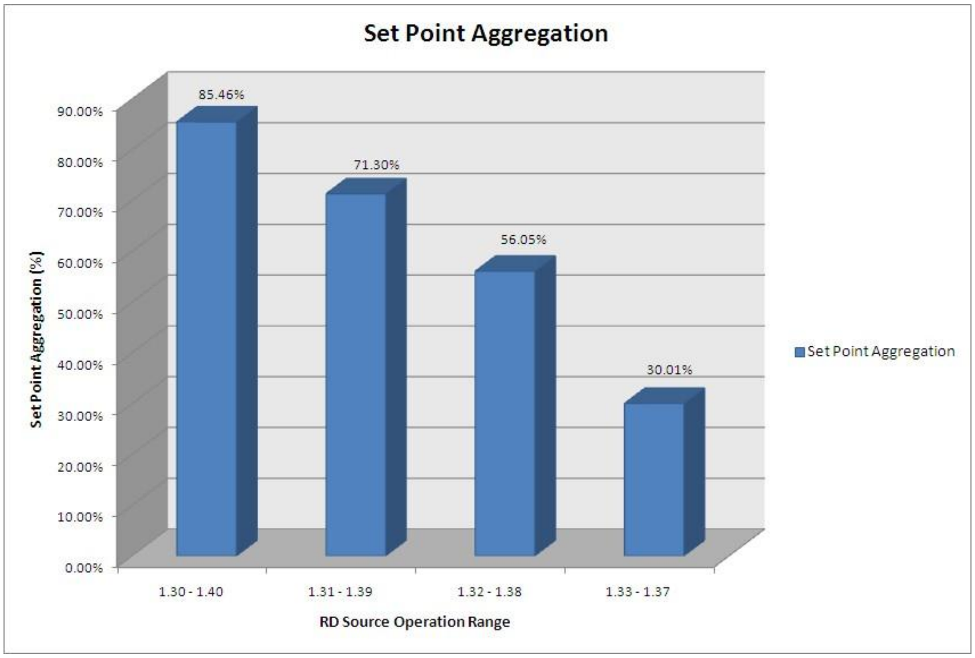

Figure 70: RD range sensitivity analysis set point aggregation

In conclusion, the operation range of the separation density within the DMC has a great effect on the quality ash control. The smaller the operation range the greater the decrease in performance. For the rest of the sensitivity analysis the RD operation range will be fixed between 1.3 and 1.4.

7.3.2.2 OPTIMISATION DELAY SENSITIVITY ANALYSIS

The GG1 operator responsible for the adjustment of the separation RDs, manages the manual control based on the target ash profile calculated in the SBS. Process time lags play a problematic role in the accuracy of the ash control, as an adjustment on the RD source is in some instances only visible after fifteen minutes. As mentioned in chapter 2, a trail-and-error method is used to control the ash quality. Contributing to the inefficient control is the fact that the magnetite recovery control loop undergoes the same degree of adjustment at the same time. If the operator detects a need for a set point change, a step change is introduced to all five modules.

The focus of this sensitivity analysis will fall on the influence the delay between each RD adjustment has on the ash quality control. Each optimisation run has a different optimisation delay. For the first run, the delay is zero minutes, implicating that the RD variables adjust every execution. The delay for the second optimisation run is

5 minutes, the third run 10 minutes and the last run is 15 minutes. These delay values were chosen to give a more realistic representation of the process the AREA04. The four optimisation runs will give a clear indication of the influence the delay has on the control performance.

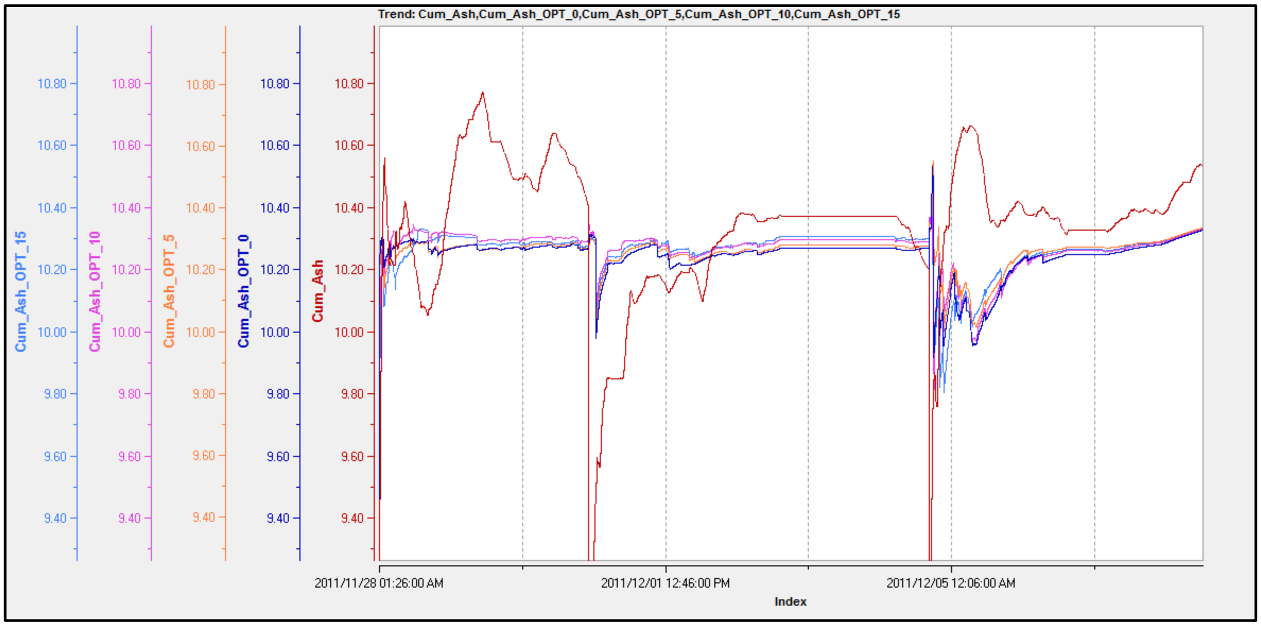

Figure 71: Ash accumulation on stockpiles with different optimisation delays

In contrast to the previous sensitivity analysis, the different optimisation delays have little influence on the ash quality on the stockpiles. Compared to the actual ash accumulation profile, little to no fluctuation is present in the first and second optimisation runs. The third optimisation runs have some disturbances at the beginning of the stockpile stacking; however, the performance is better than the actual accumulation and the different optimisation runs do not differ as much. This gives a stable ash quality production and final stockpile average ash content closer to the set point than the actual stockpile stacking process.

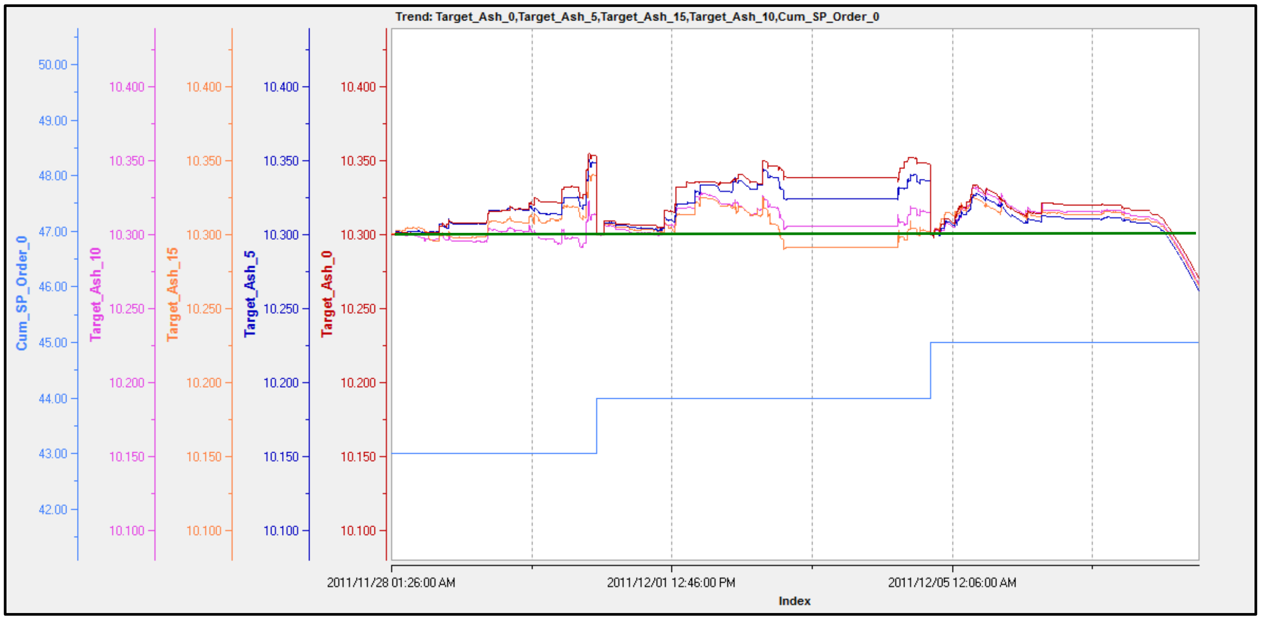

Figure 72: Target ash profiles for different optimisation delays

To support the accurate ash accumulation profiles, the target ash profiles (figure 72) also indicate good control. No extreme difference between the set point (green indicator) and the target ash values is present. In other words, less "effort" is needed to optimise the RD values in order to obtain ash quality coal in the region of the set point. Lower fluctuation brings forth worse quality coal losses.

RDPresent_A04_M1 profiles for different optimisation delays are included in the multiple-trend graph in figure 73. The top trend represents the RD profile with an optimisation execution rate of zero (red). The delay differences between the optimisation runs are apparent when comparing the first optimisation run (red) with the fourth run (pink). The fourth optimisation run adjusted the RD values every 15 minutes. This delay is more realistic to what happens in the manual control on the RD sources at GG1. The configuration of the SBS aggregates the data records into five-minute intervals. Thus, the operator can only see the result of a RD source adjustment five (blue trend), ten (orange trend), or fifteen minutes after the set point change.

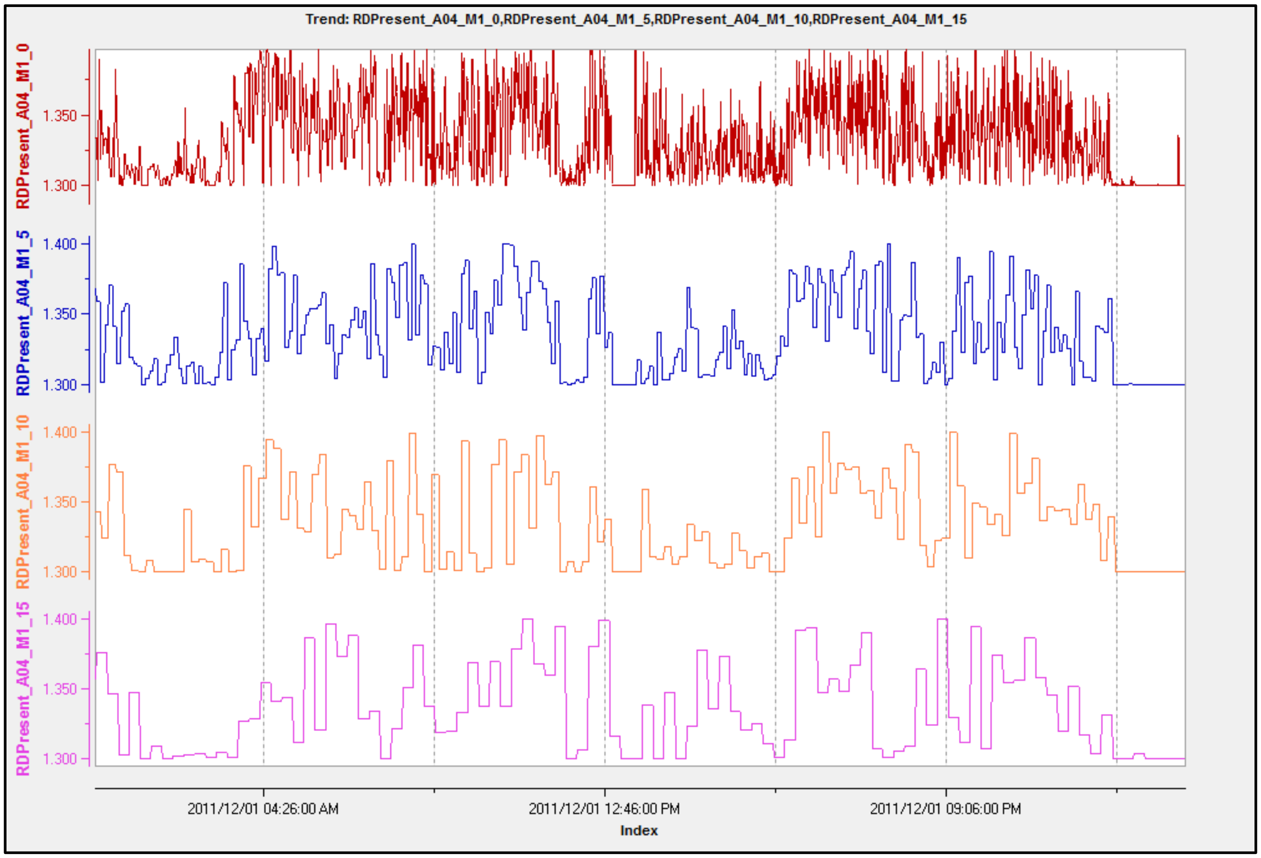

Figure 73: RD source profiles for different optimisation delays

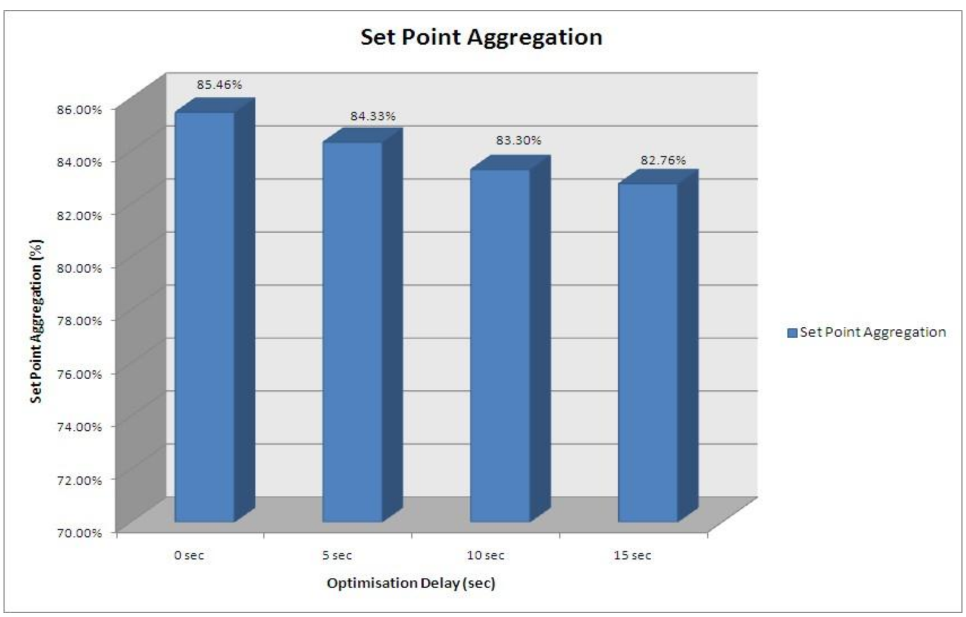

Figure 74: Set point aggregation for optimisation with different delays

The minimisation of the cost function for the different optimisation runs, over the data records of stockpiles 43 to 45, respectively, are accurate. A difference of 2.7% in data aggregation exists between the run without any delays and the run with a fifteen-minute delay. In the fourth optimisation run 82.76% of the optimised ash data fall within the 10% to 10.6% aggregation band. The time delay between RD source adjustments has little influence on the accuracy of the optimised ash quality control.

7.3.2.3 RD SET POINT CHANGE SENSITIVITY ANALYSIS

The control operator responsible for the quality control of the coking coal stockpile uses a trail-and-error method for controlling the average ash content on the stockpile. In other words, the operator will typically adjust the RD set points with a small increment (depending on the target ash value), wait for a few minutes (usually fifteen minutes) and decide on the magnitude of the next set point change. RD set point change ranges from 0.001 to 0.03. The average RD adjustment increment on the separation density is 0.002. Thus, on average the operator will adjust the RD set points by 0.002.

The aim for this sensitivity analysis is to replicate this concept of small incremental RD set point changes. For every RD value a RD lower and upper limits exist. The magnitude of change (indicated on figure 75 as the maximum RD change) from the present RD value to the lower or upper limit, serves as the sensitivity variable for this analysis. The range from the lower to the upper limit for a specific RD value is the optimisation range for the next optimisation execution. The magnitude of change varies from 0.001 (first optimisation run) to 0.01 (fourth and final optimisation run) in 0.003 increments for this sensitivity analysis.

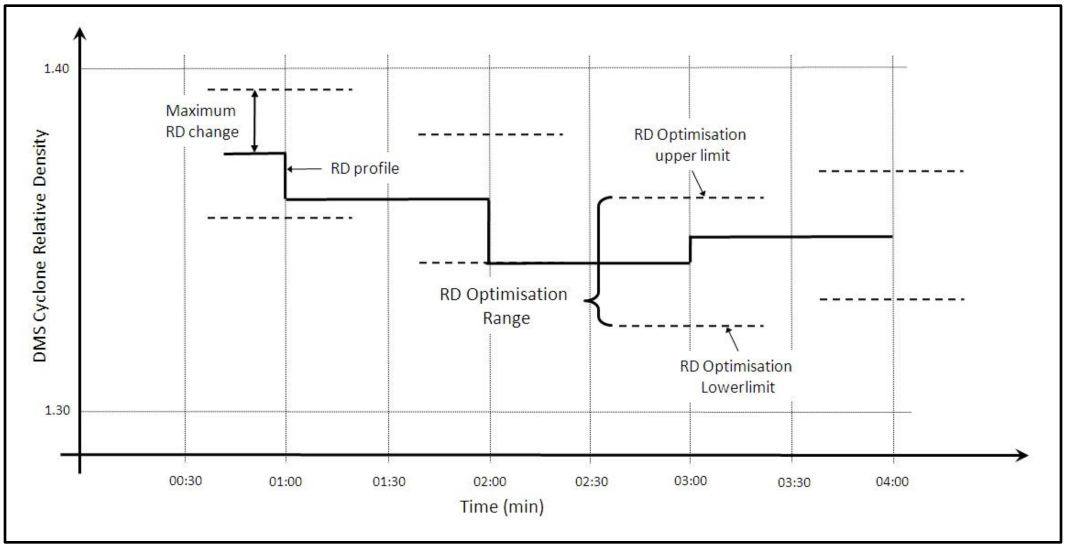

Figure 75: Variable RD Optimisation Limits with Fixed Optimisation Range

For illustrating the influence this magnitude of RD changes has on the accuracy of the control, figure 76 compares the actual ash accumulation on stockpiles 43 to 45 to the ash accumulation of the optimisation runs. The multiple-trend graph shows the more accurate quality control and the different RD optimisation ranges have very little influence on the accuracy of the control. The results from the first optimisation run show the greatest deviation compared to the rest of the optimisation runs' results. As for the target ash profiles for the four optimisation runs, figure 77 shows good quality control around the set point.

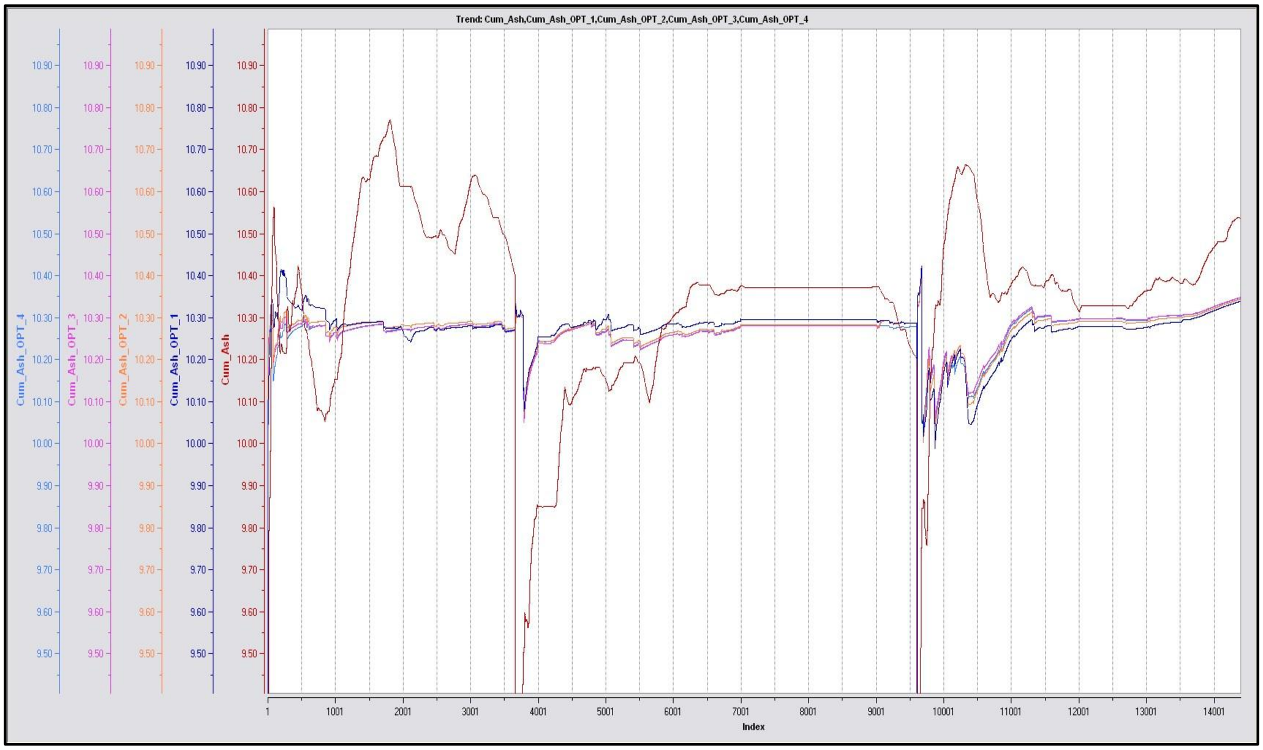

Figure 76: Ash accumulation on stockpiles for different magnitude of RD changes

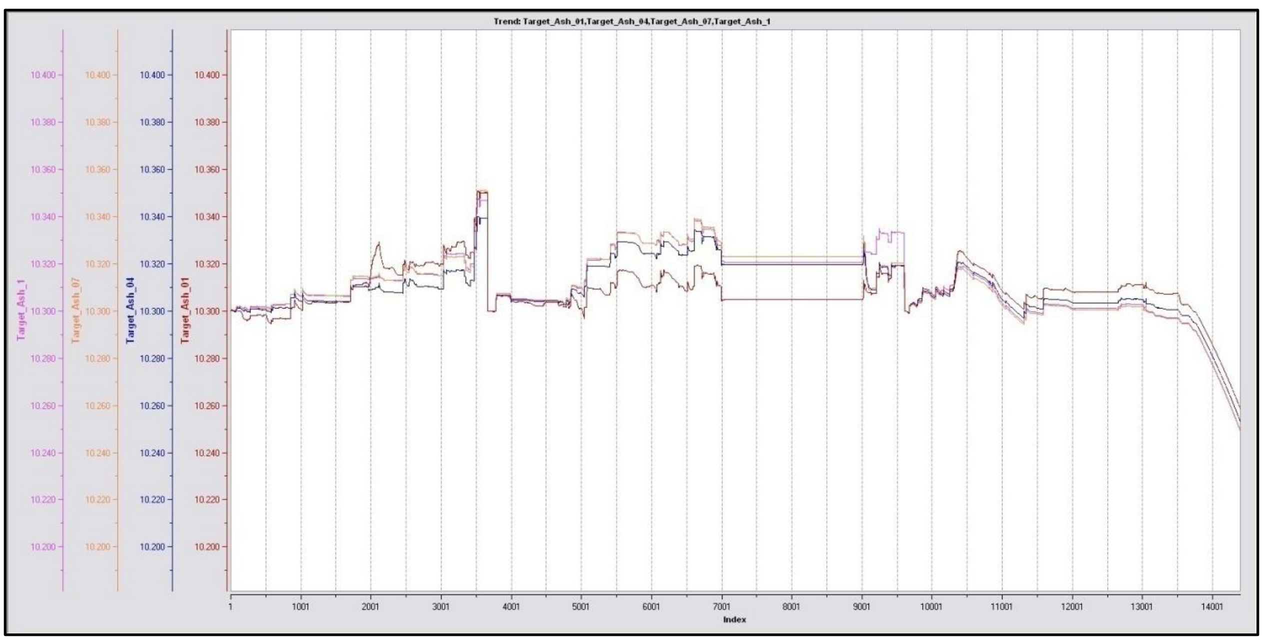

Figure 77: Target ash profiles for different magnitude of RD changes

The effect of the different RD optimisation ranges on the RD profiles for the different optimisation runs is apparent in figure 78. The RD values measured on the first module

DMC for the different optimisation runs are trended in figure 78. The region encircled in green shows the effect of the different ranges more clearly. The optimisation run with the smallest optimisation range (first optimisation run trended in red) shows less fluctuations than the rest of the optimisation runs' results.

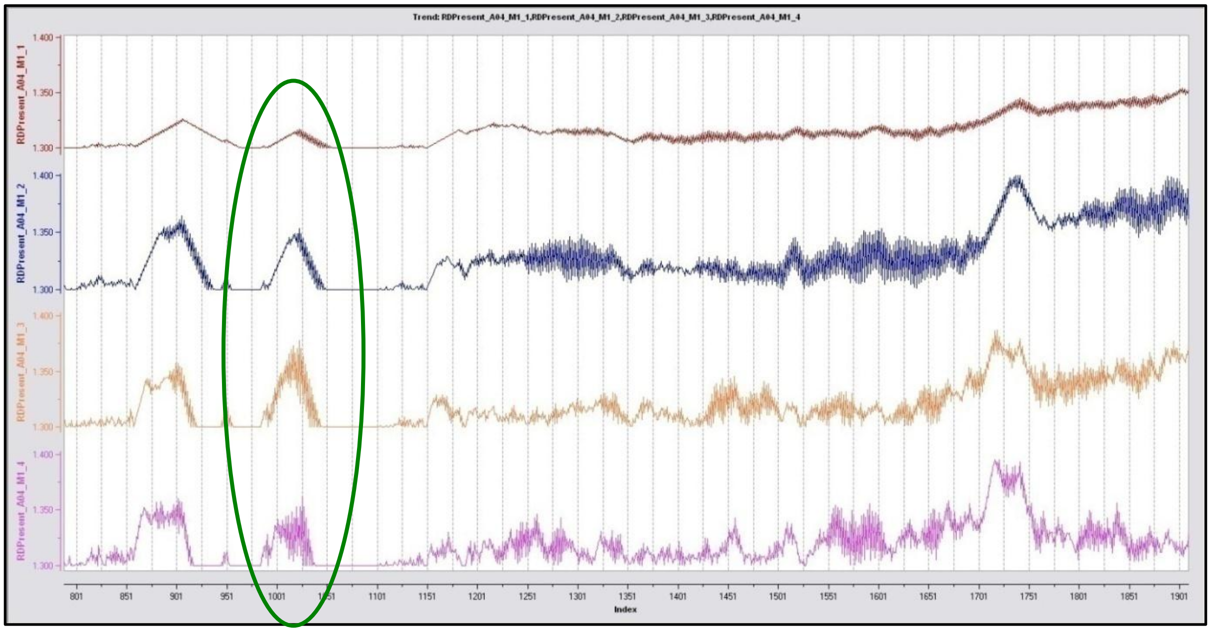

Figure 78: RD optimisation profiles for different magnitude of RD changes

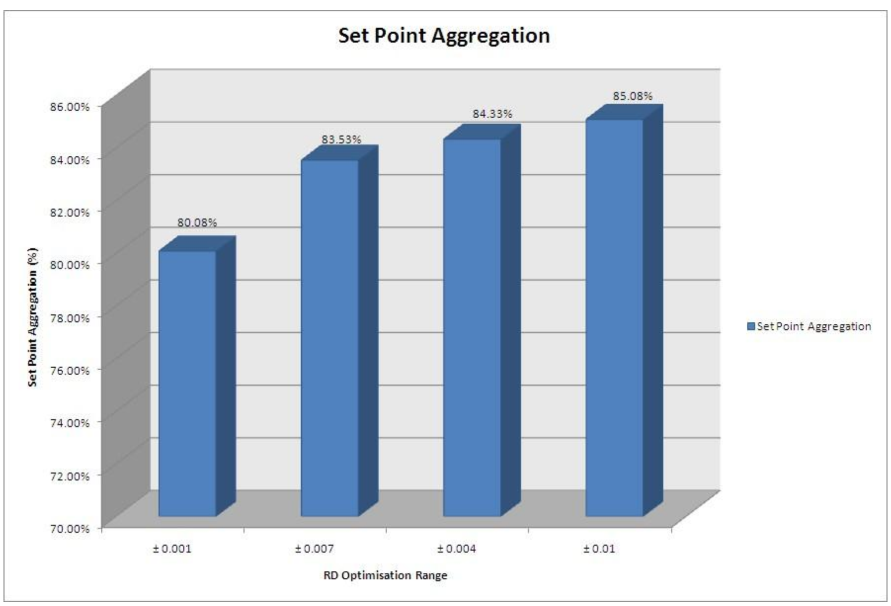

Figure 79: Set point aggregation for optimisation with different RD change magnitudes

The set point aggregation bar chart in figure 79 confirms the observations made on figure 78. The first optimisation run with a RD change limit of 0.001 produced less accurate results than the rest of the runs. Yet, the first optimisation run is more accurate compared to the results from a fixed RD range between 1.33 and 1.37. In conclusion, the size of the RD change does not influence the accuracy of the ash content optimisation as much as the altering of the RD range as a whole (RD Range Sensitivity Analysis).

7.4 FEASIBILITY ANALYSIS

The stage is set to conclude the theoretical benefits of an optimised control on the GG1 coking coal production line. The sensitivity analysis done in the previous section gave insightful knowledge on the capabilities and limitations of the optimisation solution. The sensitivity analysis also made way for testing the optimisation solution with realistic parameters more relevant to the actual manual control at GG1. The focus of the feasibility analysis is to quantify the comparison results between the actual process and the optimised (and more realistic) solution. From the quantified results, conclusion can be drawn on the feasibility of such an optimised control.

For comparing the efficiency and throughput of the current quality control against an optimised control, it is important to optimise the quality control integrated with realistic characteristics relevant to the actual control at GG1. In producing such an optimised solution, the optimisation run included the parameters as listed in table 27. From the result determined in the sensitivity analysis, the RD operation range was kept at 1.3 to 1.4. The execution rate is kept at one minute, the same as the sampling rate of the real time measurements. In reality, this means that the optimised controller will make the necessary RD adjustments every minute and not wait fifteen minutes as in the case of the current quality control. The value for the maximum optimisation RD change was fixed at 0.002 since the average set point change for the current control is 0.002.

Table 27: Realistic optimisation parameters

Parameter	Value
RD operation range	1.3 – 1.4
Optimisation delay	5 minutes
Maximum optimisation RD set point change	0.002

Figure 80 illustrates the comparison between the ash accumulation (red) and optimised ash accumulation (blue). The optimised ash accumulation is much more stable than the actual ash accumulation. This indicates good quality coking coal going to waste due to fluctuation in ash production brought on by the current manual control. Table 28 compares the results from the optimisation solution and actual current data. On all three stockpiles, the optimised results are closer to the set point of 10.3%. The results from the ash accumulation underscore the improvement of the optimised control on the current manual control.

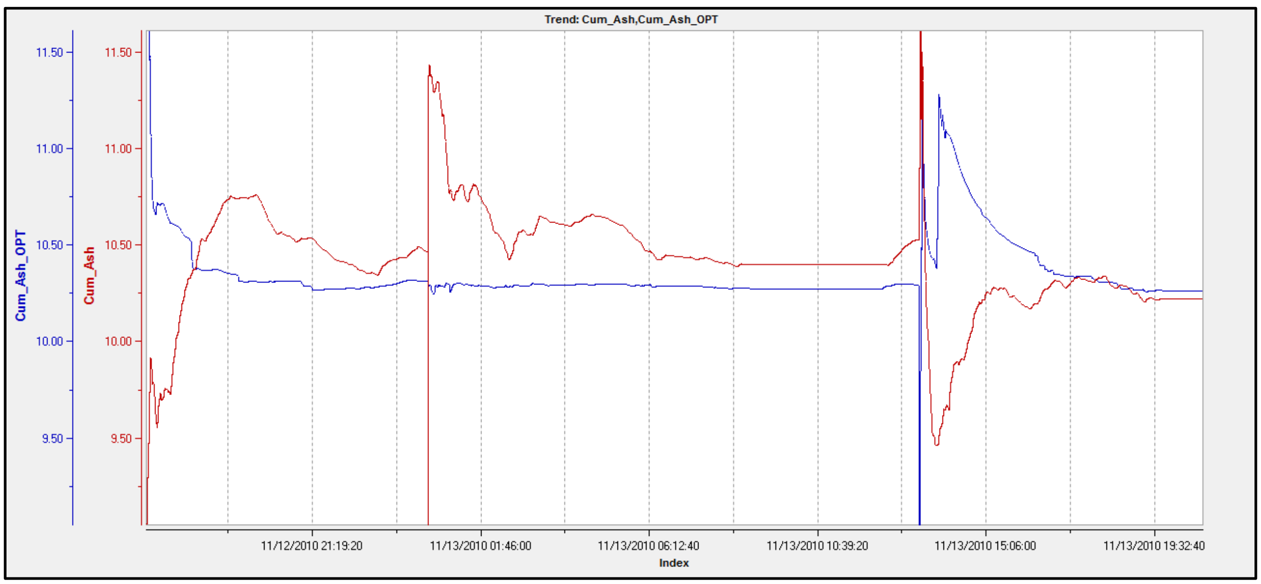

Figure 80: Ash accumulation comparison between corrected and optimised ash

Figure 81 compares the mass accumulation of the optimised coking coal production (blue) to the mass accumulation as determined with the actual mass flow values (red). The yield of coking coal from an optimised solution is higher than the current yield. On average, for the three stockpiles investigated, a yield increase of 9.8% was reached.

According to a communication with a senior metallurgist at GG, it is safe to assume the price for coking coal to be R600/ton (Rautenbach, 2010b). 2.63 million rand was raised applying this assumption to the yield increase, the cost for the three stockpiles combined. The results from the cumulative mass per stockpile comparison are listed in table 28.

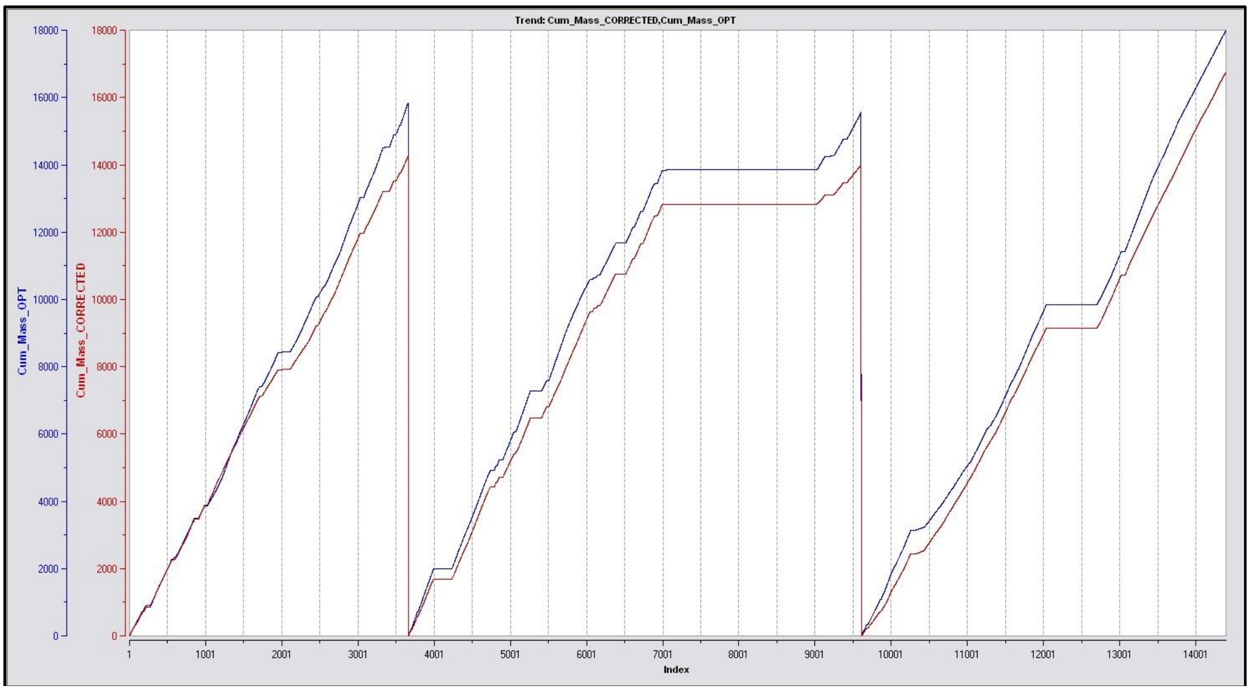

Figure 81: Mass accumulation comparison between corrected and optimised mass

Table 28: Benefit estimation results

Stockpile	Cumulative Ash (%)		Cumulative Mass (Tonnes)	
	Optimised	Actual	Optimised	Actual
2K02692 (43)	10.265	10.405	15857.6	14270.5
1K02693 (44)	10.287	10.388	15557.5	14001.0
2K02694 (45)	10.344	10.530	18003.6	16756.8

In evaluating the generalisation potential of the optimisation solution, the Group2 and Group3 data were also optimised and assessed, using the same optimisation parameters as with Group1. The ash accumulation determined from the Group2 data shows again good control around the set point (figure 82). This shows a good generalisation of the optimisation solution concerning the Group2 data. Stockpile 47 and stockpile 48 shows some poor performance, deviating from the set point with greater fluctuations. The comparison results on the Group2 and Group3 evaluation are sorted in table 29. In viewing the mass accumulation for the same stockpiles in Group2 (figure 83), lower throughput is apparent in most stockpiles. The throughput ultimately determines the profit collected per stockpile. A lower throughput results in a financial loss.

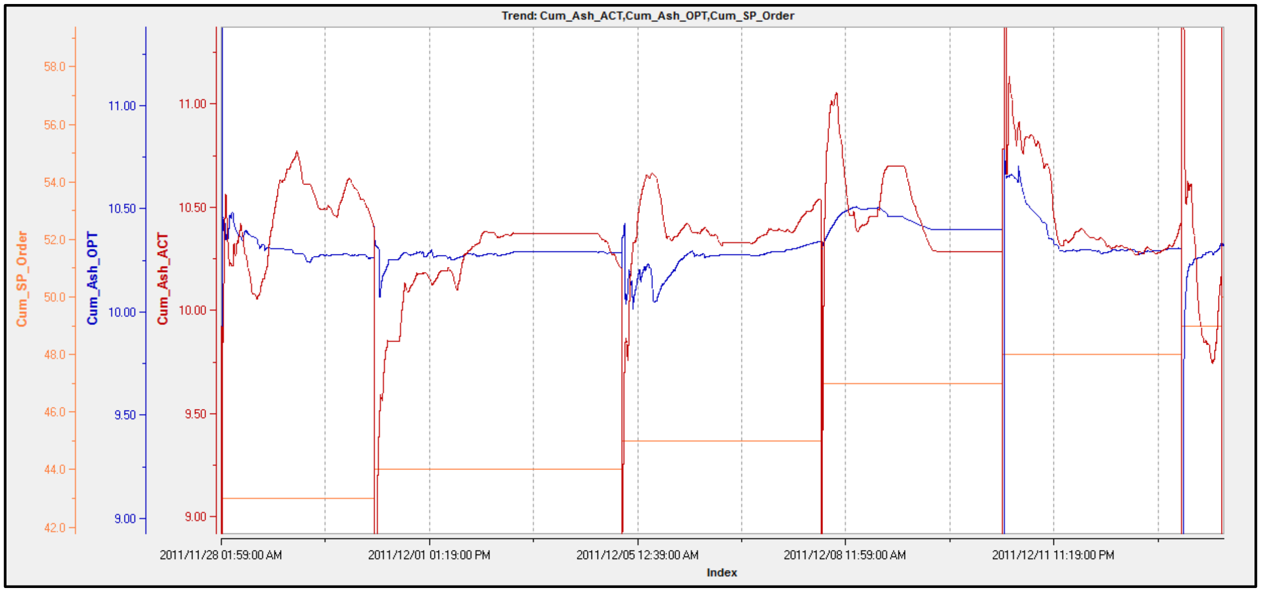

Figure 82: Ash accumulation comparison of corrected ash vs. the optimised ash of Group2

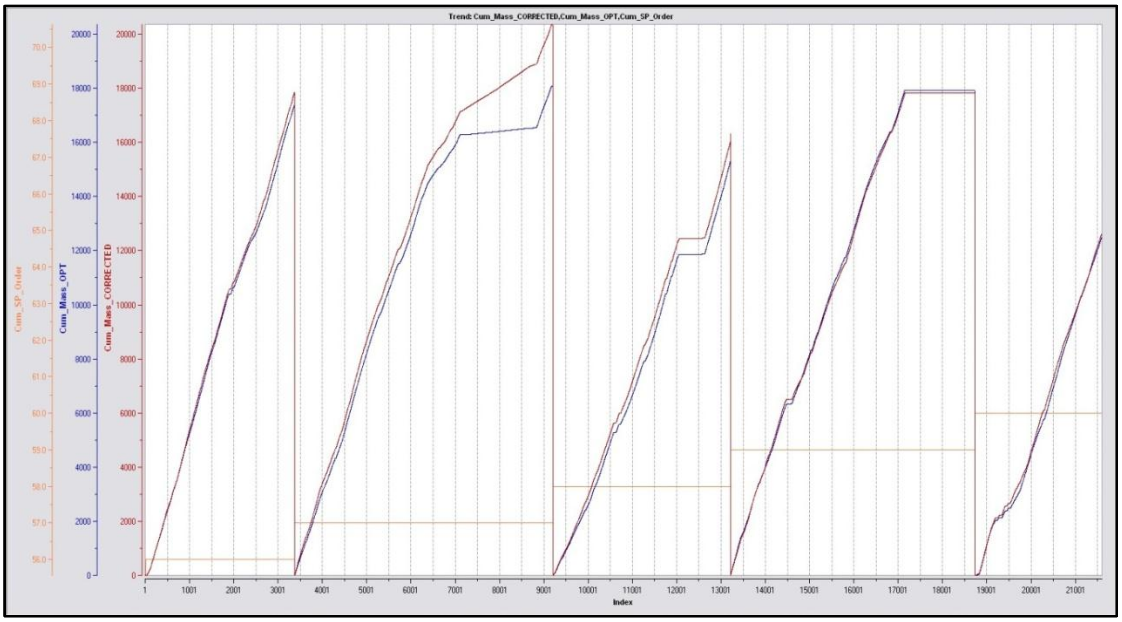

Figure 83: Mass accumulation comparison of corrected mass vs. optimised mass of Group2

Results from the Group3 data evaluation show poorer optimisation performance. The ash accumulation depicted in figure 84, shows deviation from the set point as well as greater fluctuations. Figure 85 shows the lower throughput produced by the optimisation solution. These results highlight the necessity for improvement on the models generated in the data mining, as well as the optimisation solution itself.

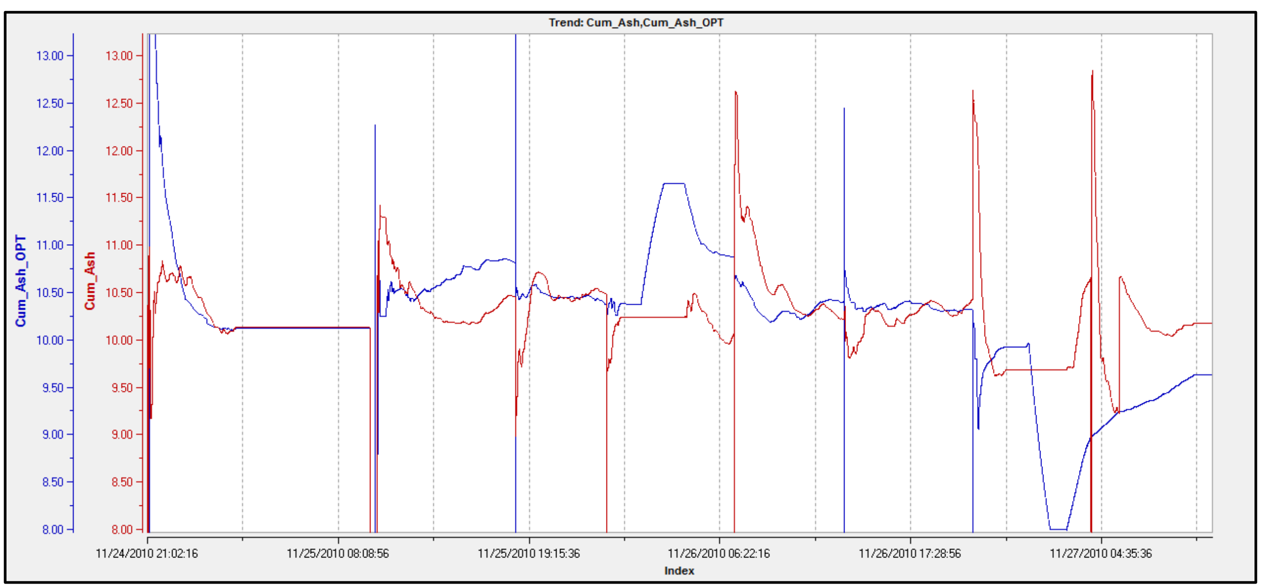

Figure 84: Ash accumulation comparison of corrected ash vs. optimised ash of Group3

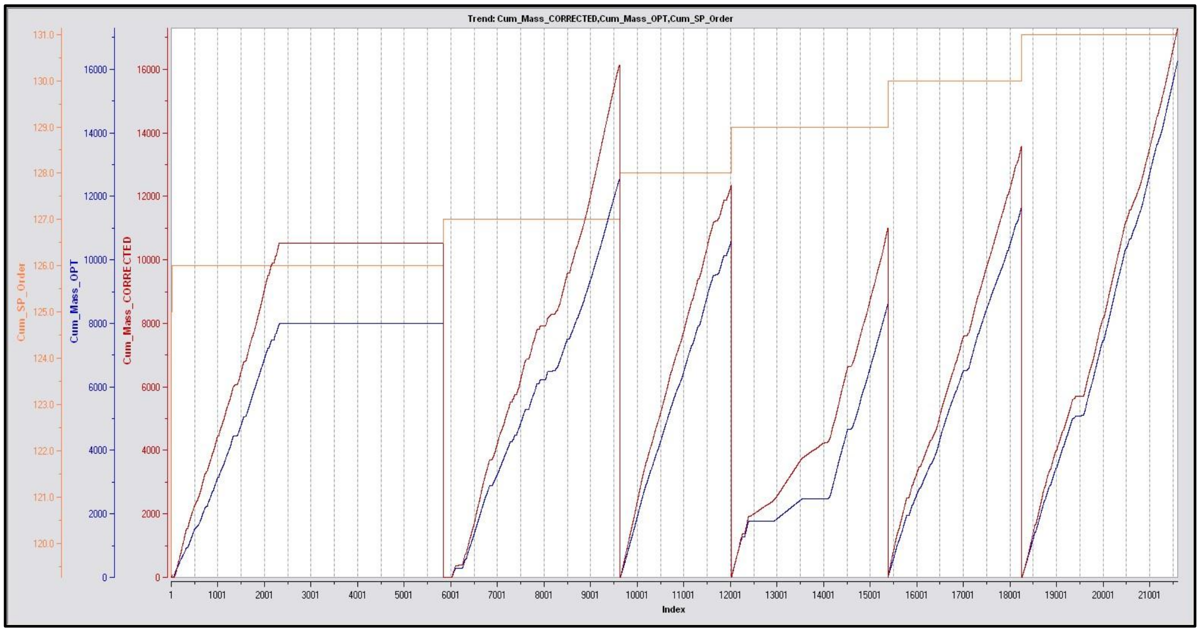

Figure 85: Mass accumulation comparison of corrected mass vs. optimised mass of Group3

Table 29: Feasibility analysis results for Group2 and Group3

	Cumulative Ash (%)		Cumulative Mass (Tonnes)	
Stockpile	Optimised	Corrected	Optimised	Corrected
		Group2		
1K02704 (56)	10.31	10.42	17423.70	17872.37
3K02705 (57)	10.29	10.47	20359.17	18076.65
2K02706 (58)	10.28	10.30	15336.37	16345.61
1K02707 (59)	10.34	10.34	17935.15	17833.04
2K02708 (60)	10.50	10.11	12504.69	12631.14
		Group3		
4K02772 (126)	10.12	10.22	7988.77	10536.06
1K02773 (127)	10.81	10.40	12524.69	16140.25
3K02774 (128)	10.37	10.40	10623.76	12379.61
1K02775 (129)	10.87	10.04	8602.50	11019.26
3K02776 (130)	9.99	10.39	11642.62	13592.02
1K02777 (131)	10.35	10.33	16270.91	17299.18

Figure 61 and figure 62 illustrate the efficiency of an optimised control strategy. The optimisation solution was able to control the ash content around the set point with very little fluctuations. Due to this decrease in fluctuations, and increase in optimum separation RD control the yield of the process increased implicating an increase in revenue per year. However, fluctuations visible in the Group3 optimised results indicate room for improvement.

The improvement brought on by the optimisation approach can be measured by comparing the average percentage ash and mass flow as well as the variance in percentage ash. Before optimisation the average percentage ash in Group2 was 12.8

Deviation of the average ash content of a stockpile from client specifications may lead to penalties. As with the optimised control, penalties can be avoided more efficiently. A more stable coking coal quality is favourable to the client. For GG the client is the steel manufacturing industry. As discussed in chapter 1, coking coal is converted to coke, which is essential for the iron-making process. The conversion of coking coal to coke entails driving off coal impurities to produce almost pure carbon. High impurity content in the coal (proportional to high ash content), is damaging and unfavourable to the coke ovens.

Another factor stressing the importance of good and stable coking coal quality is the fact that the coke rate is directly dependent on the coal quality. Decreasing the coking rate usually increases product quality. Higher more stable coal quality control is profitable to the client and thus, financially beneficial for the provider, as proven with the higher mass accumulation on stockpiles (Çoban, 1991).

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

8.1 INTRODUCTION

The KD process explained in the literature review in chapter 3 functioned as the backbone of the quality control investigation. Chapter 4 introduced the first step in the KD process and defined the problem statement, the structure of the investigation based on the KD process step, and the data applicable to the problem environment. Chapter 5 saw the evaluation of the quality of the data using several techniques and visualisations. The number of data records was reduced to several stockpiles worth of sequential data records. This data pre-processing step prepared the data for more accurate and representative model generation. The data mining stage was responsible for the intelligent algorithm extracting elemental process knowledge. NN models were generated on the data from the identified stockpiles to simulate the performance of the mass flow and ash content on the coking coal product line. The different models on the three data groups were compared in order to decide on a suitable model for further analysis. Interesting behaviour from the process inter-variable relationships were identified and discussed. Chapter 6 produced good results in terms of model generation accuracy.

Chapter 7 used the gained knowledge to realise the theoretical benefits of an optimised manual quality control. The current manual control results were compared to the control of the optimisation solution. The optimisation solution produced stable and more accurate results, as illustrated in the previous chapter. This chapter summarises the investigation results and includes several recommendations.

8.2 GG1 CURRENT COKING COAL PRODUCTION

Several key factors were identified that contribute to the inefficient quality control on the coking coal production line. Some recommendations are included in the following conclusions:

- For manual quality control inducing variance to the product-line ash quality, the secondary DMCs in AREA 04 can produce a coal product with ash content lower than the ash content set point. Thus, the ash content of the coal on the product line is lower than it should be. This means that the sinks in the DMC contain coals with ash content of 10% and ultimately a loss of good quality coal. These coals are sent to Matimba Power Station along with the accompanying metallurgical coal. On the other hand, if the beneficiation DMCs in AREA 04 produce floats with ash content higher than the set point, the poor quality coal ends up on the product stockpile and an increased density is necessary in the DMC in order to compensate for the low quality coal on the stockpile. In addition, the fluctuations result in a decrease in yield as explained in section 2.3. The control of DMCs producing a coal quality with less fluctuation is a supported control strategy as proven from literature in section 2.3. Fortunately, results generated from section 7.4, indicate that the optimisation solution is able to increase the yield with the optimum control of the separation RDs. Lower fluctuations occur due to the optimisation, indicating the less valuable coal is sent to the power station. On the other hand, less poor quality control is introduced to the coking coal stockpile.
- Several assumption were made due to a lack of process information:
    - The optimisation is done on the RD of the dense medium and not on the set point as determined by operator control. In the optimisation approach, it is assumed that the correlation between the RD set points and the actual separation RD values are at a maximum. This is not the case for online operation. The separation RD values occasionally deviates from the set point.

    - The efficiencies of the sieves upstream from the DMC banks are unknown. Thus, the mass split at the sieves are assumed negligible and the mass flows measured on the belt scales are the same mass flows feeding the DMCs.
    - The operation performance of AREA05 at GG1 is also unknown. A product stream from the spiral classifiers with unknown mass flow and ash content is combined with coking coal product line. The coking coal line from the spiral classifiers will have an influence on the mass flow and the ash content of the final coking coal product line.

  Information relevant to the assumptions made could increase the accuracy of the optimisation approach as well as the optimisation solution.
- The investigation conducted by Addison *et al* (2010) saw better DMC quality control with the implementation of sensors on the floats and the sinks of the relevant DMCs. This implementation is not available at GG1 and may go a long way in the increase in DMC control efficiency.

8.3 SBS EVALUATION

The SBS plays an integral role in the stockpile management at GG1. This system is responsible for using the mass flow, ash monitor readings and the results from the LIMS database in the quality management of the stockpiles. The SBS produces several outputs necessary for manual quality control on the average ash content of the coking coal stockpiles. Numerous factors in the SBS contribute to the reduced integrity of the quality control.

- The SBS aggregates data records to five-minute and hourly samples. This initiative allows for the updating and integrating of the ash bias in the SBS outputs. The operator receives readings every five minutes. On average 19.09 tonnes of coking coal is stacked on the stockpile in every five-minute period. Adding to the inefficiency is the fact that the operator is able to notice a change at five-minute intervals whereas a set point increase could be noticed within one minute. Altering the sample rate to one-minute as currently logged by the measuring instrument, the operator will be able to control quality more rapidly.

- The operator is responsible for the quality control on a coking coal stockpile. This responsibility entails the evaluation of accumulated ash content per stockpile in order to adjust the DMC separation RDs. It is recommended that the evaluation strategy be converted to the SBS user interface indicating appropriate RD set point values for the specific ash operation point. This could be achieved using process models to relate the separation RDs to the ash content and system identification methods to generate transfer functions able to relate the RD set points and the separation RDs.
- A trail-and-error method is used to manage the quality of the stockpile. The operator evaluates the target ash and ash accumulation on the current stockpile and adjusts the RD set points on all five modules according to expert knowledge. The operator waits several minutes (5 minutes, 10 minutes or 15 minutes) to notice the outcome of the adjustment and adjusts the set points again according to the new readings. This is avoided with the optimisation solution. An optimum set of separation RDs set points will be available every minute. As explained in chapter 2, the operator is still in the control loop, as his experience will determine the validity of the optimised RD set points.
- The control on the coking coal stockpile quality is highly dependent on the knowledge of the operator. In case of a shift where the operator is not as competent, human error plays a major role in the efficiency of the manual control.
- The current quality control implemented at GG1 produces ash quality fluctuations in the product stream. These fluctuations lead to the wasting of good quality coking coal to the power station stockpile. In addition, to compensate for the good quality coal losses the coking coal stockpile is stacked with ash qualities higher than the set point.

8.4 OPTIMISATION RESULTS

Using the KD process as investigation methodology, historical data from the problem environment at GG1 were extracted and prepared for data mining. The data mining stage was responsible for the generation and evaluation of nonlinear models built to simulate the process. An appropriate model was chosen to further the investigation. A sensitivity analysis, benefit estimation and feasibility analysis were conducted to realise the potential of the optimisation solution.

- The optimisation performance of the CSense® Architect GA showed a degree of error when optimising the ash content. Thus, other optimisation techniques or GA parameter configuration should be investigated for the best possible optimisation algorithm.
- The results from a preliminary optimisation run were compared to the actual process data. The optimisation results showed a great improvement in stable ash production and constant average ash accumulation. 83% of the stockpiles show improvement on the current manual quality control.
- Sensitivity analyses were done on three of the stockpiles. Changes on the overall RD operation range have great influence on the performance of the optimisation solution. The delay in optimisation, as well as the magnitude of RD set point change has little influence on the optimisation solution results. These sensitivity analyses made way for a solution representing actual quality control conditions.
- An optimisation solution was built on parameters introducing realistic conditions to the quality control. The optimisation results were compared to the actual stockpile properties. The optimisation results showed a yield increase of 9.8% over the three stockpile groups analysed. Assuming a 9.8% yield increase is possible over a production year, Exxaro is able to increase revenue by R 250 million. The proposed control solution decreases the loss in good quality coking coal to the power station coal stockpile, and an increase in profit from the selling of the coking coal. A more stable quality production is possible with a decrease in standard deviation from 1.11 to 0.20. In addition to the stable quality production,

the average percentage ash is decreased from 11.28% to 10.39% (closer to the target of 10.3%) after optimisation.

- With the proposed control solution, the degree of human error can be decreased in providing the operator with the optimised RD set points generated by the optimisation solution investigated.
- It is recommended to investigate the effects of the spiral plant inputs to the coking coal stockpiles in order to realise the true environment of the proposed control solution. With knowledge of the spiral plant effects, a detailed mass balance will allow for a more accurate KD and control solution.
- With the success of such a control solution implementation, an improved solution may be implemented on all SBS's in and around GG beneficiation plants.

The optimisation solution has the ability to control the ash accumulation around a set point with minor fluctuations compared to the current control system. More information on several aspects of the coal beneficiation plant at GG1 will increase the accuracy and efficiency of this solution. More studies need to be conducted on the NN topology as well as the GA parameters.

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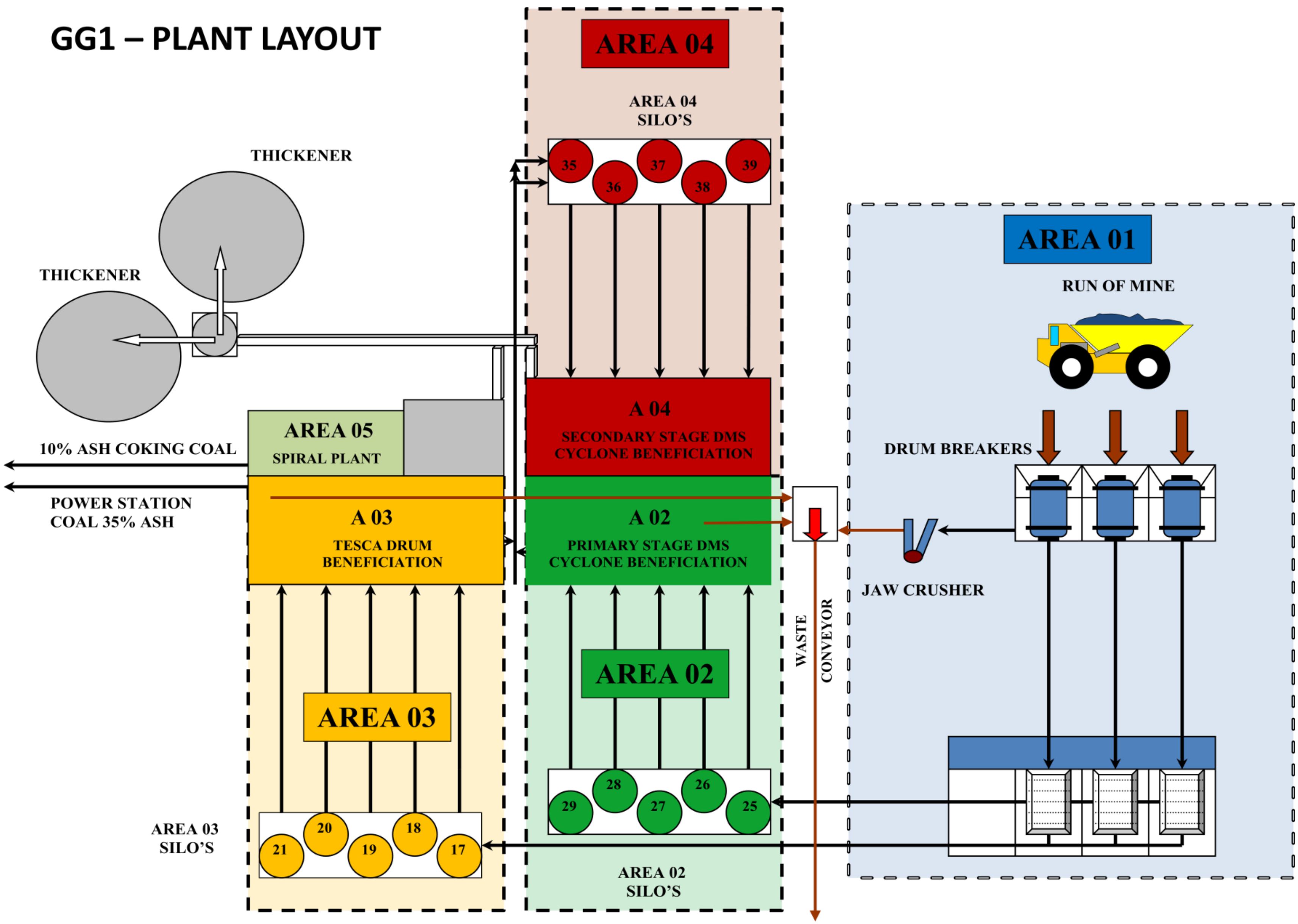
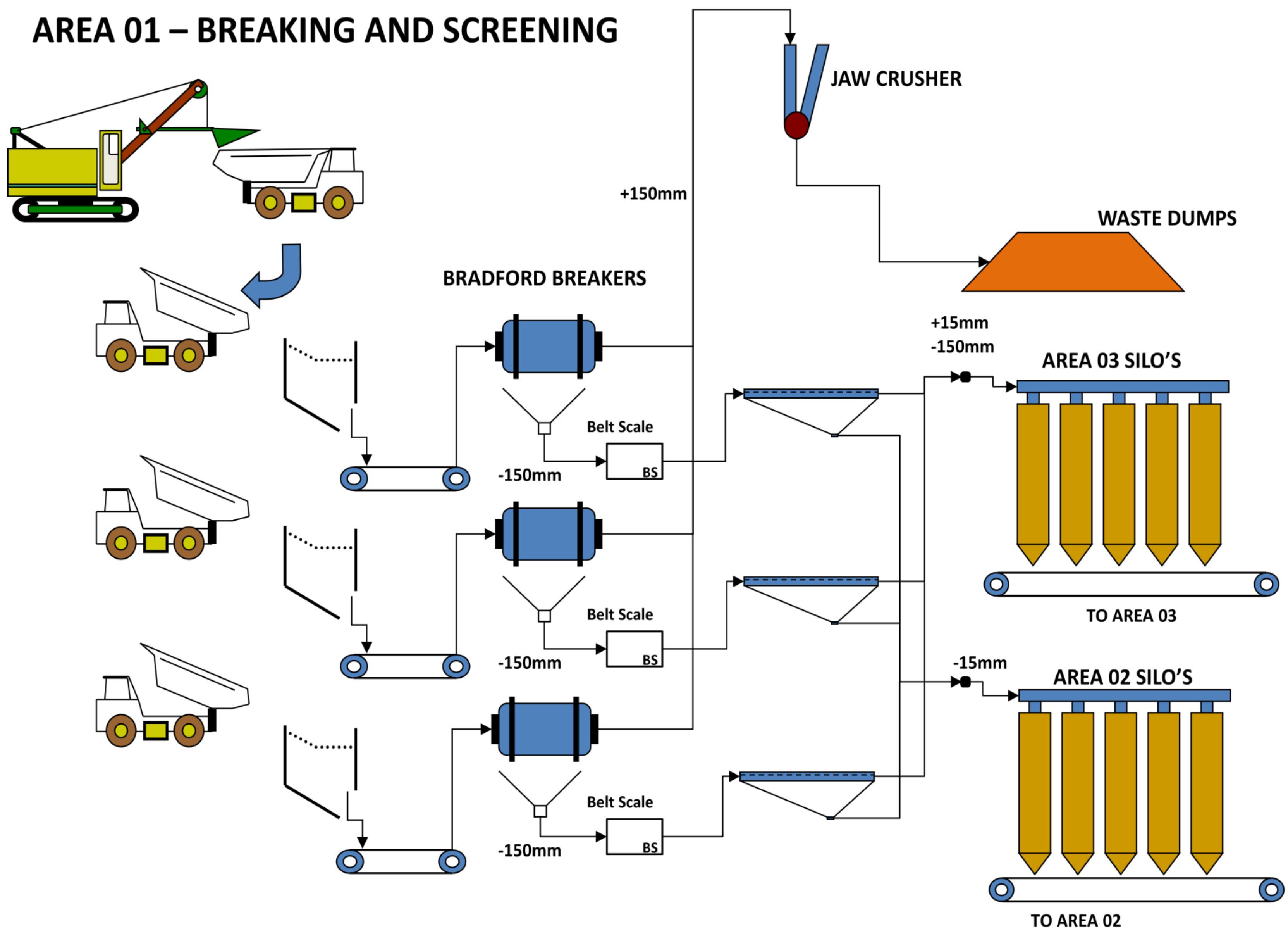
APPENDIX A

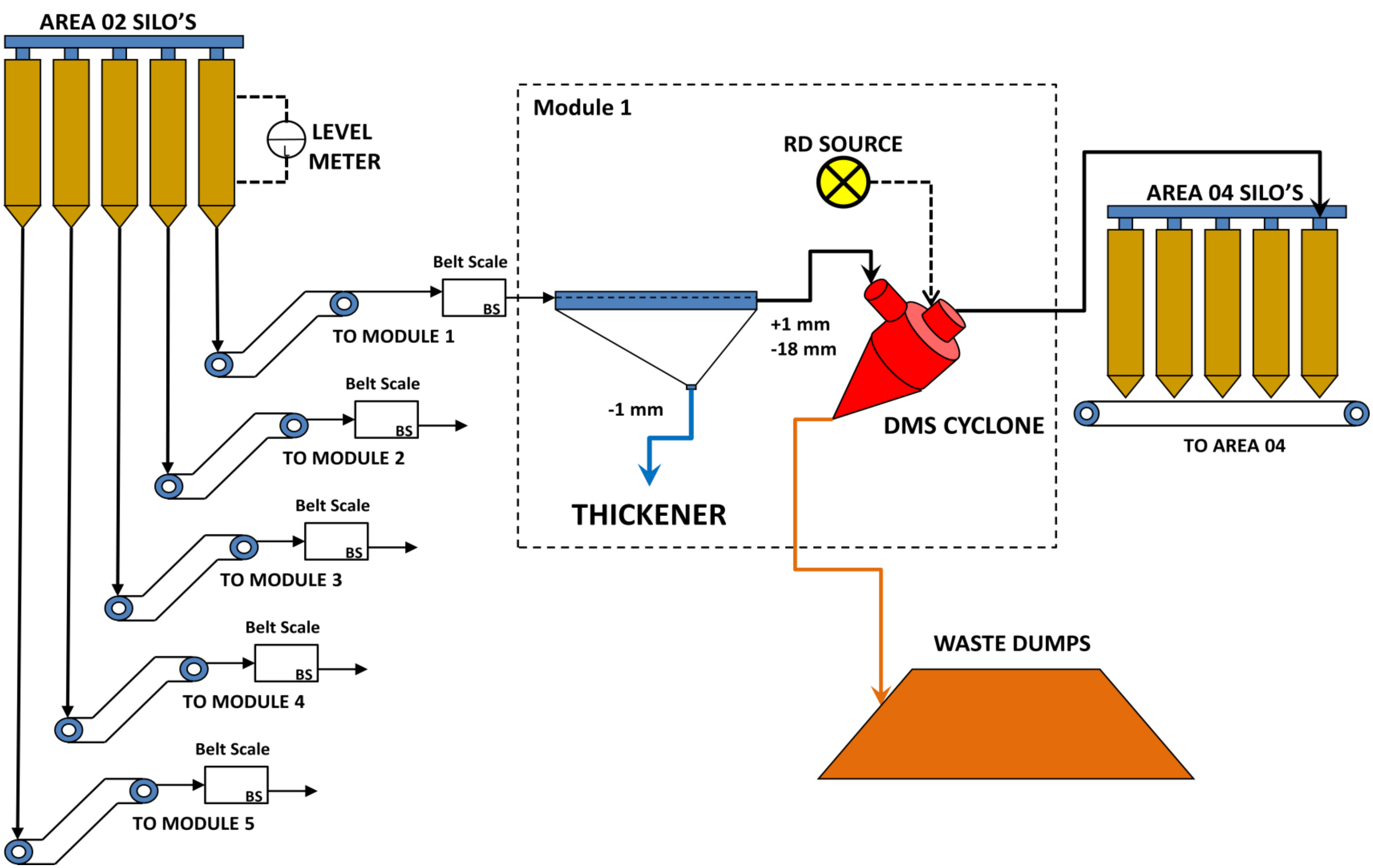
PROCESS FLOW DIAGRAM



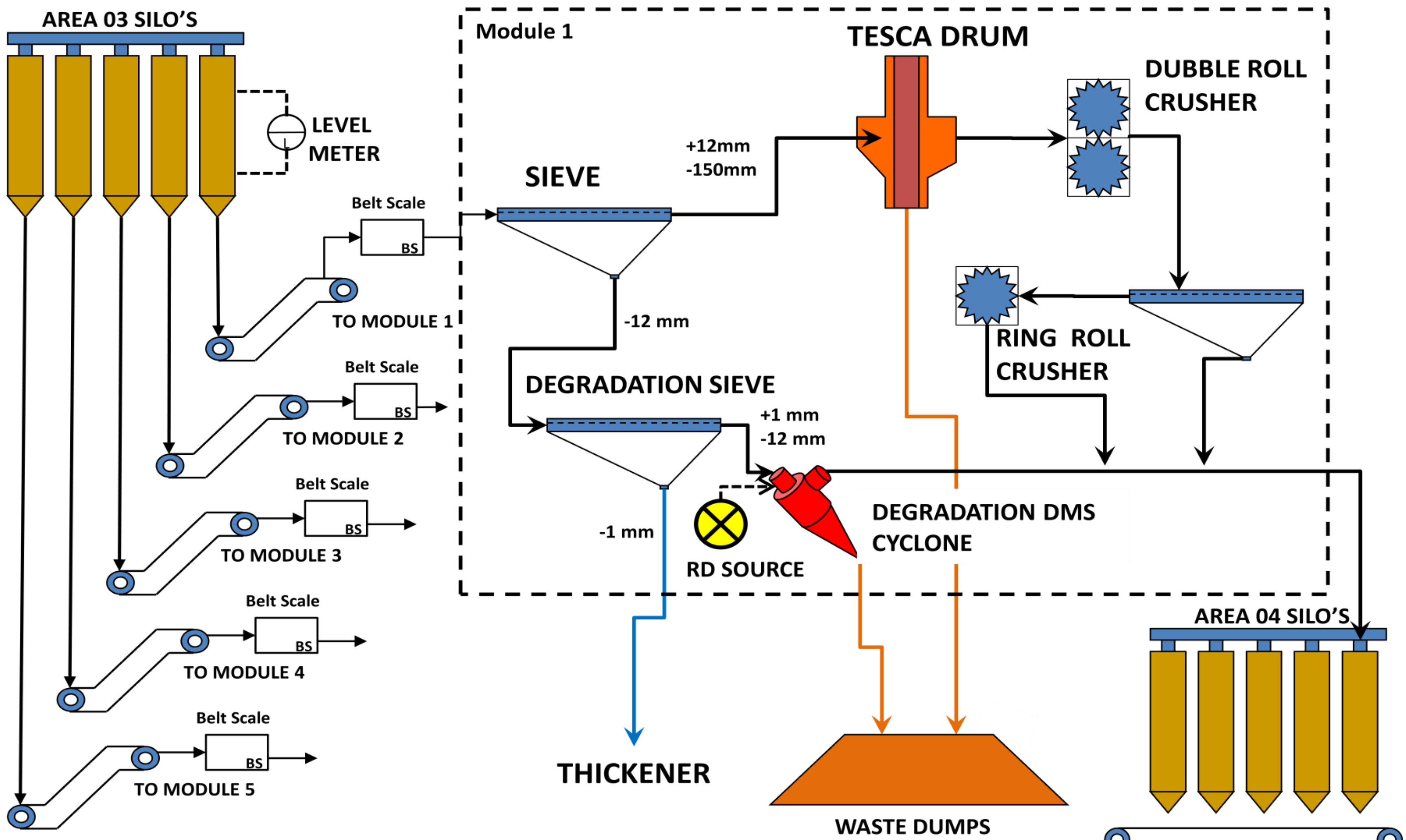
Appendix A
Process Flow Diagram

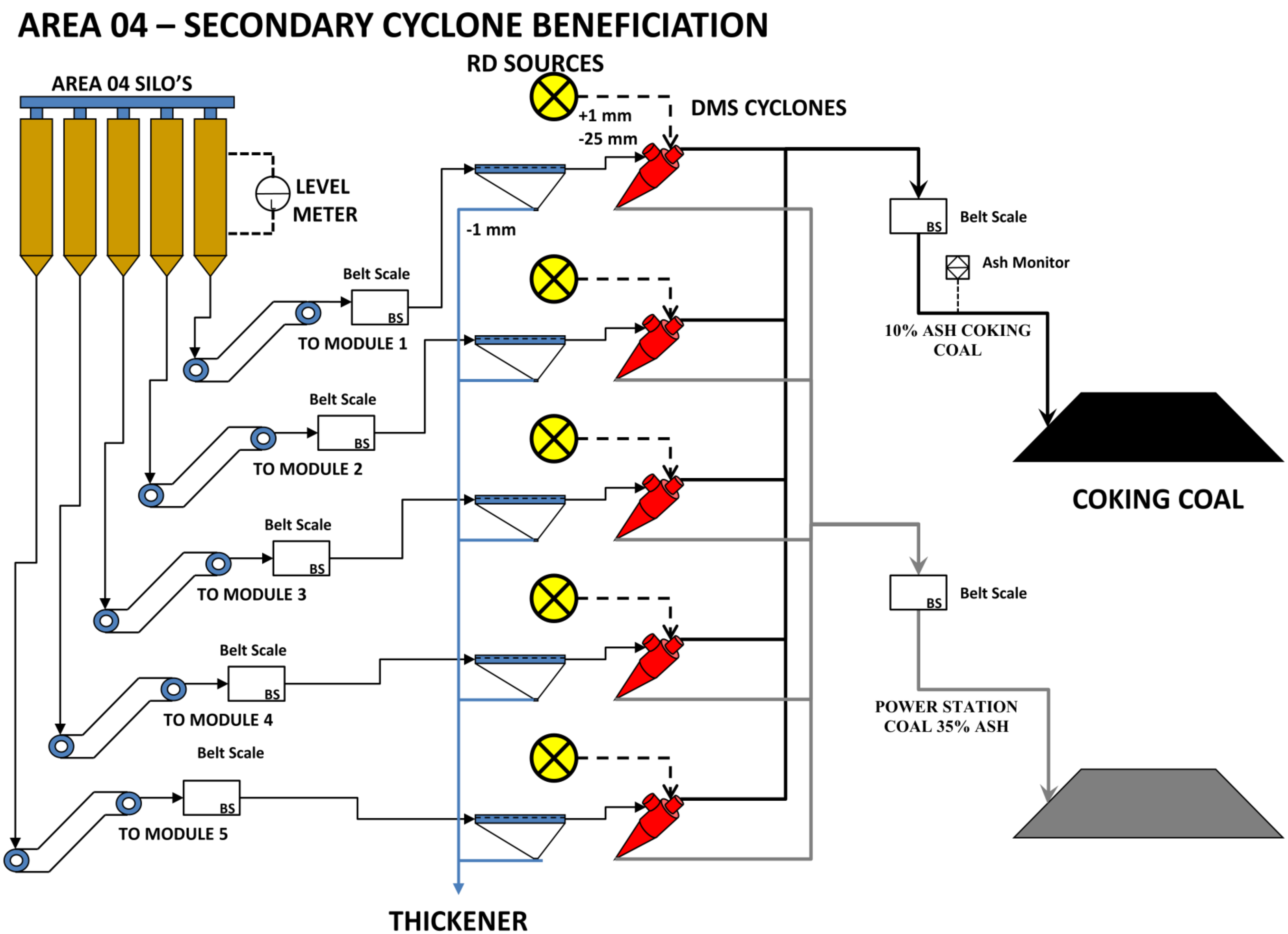

AREA 01 – BREAKING AND SCREENING
JAW CRUSHER
+150mm
WASTE DUMPS
BRADFORD BREAKERS
+15mm
-150mm
AREA 03 SILO'S
Belt Scale
BS
-150mm
TO AREA 03
Belt Scale
BS
-150mm
-15mm
AREA 02 SILO'S
Belt Scale
BS
-150mm
TO AREA 02

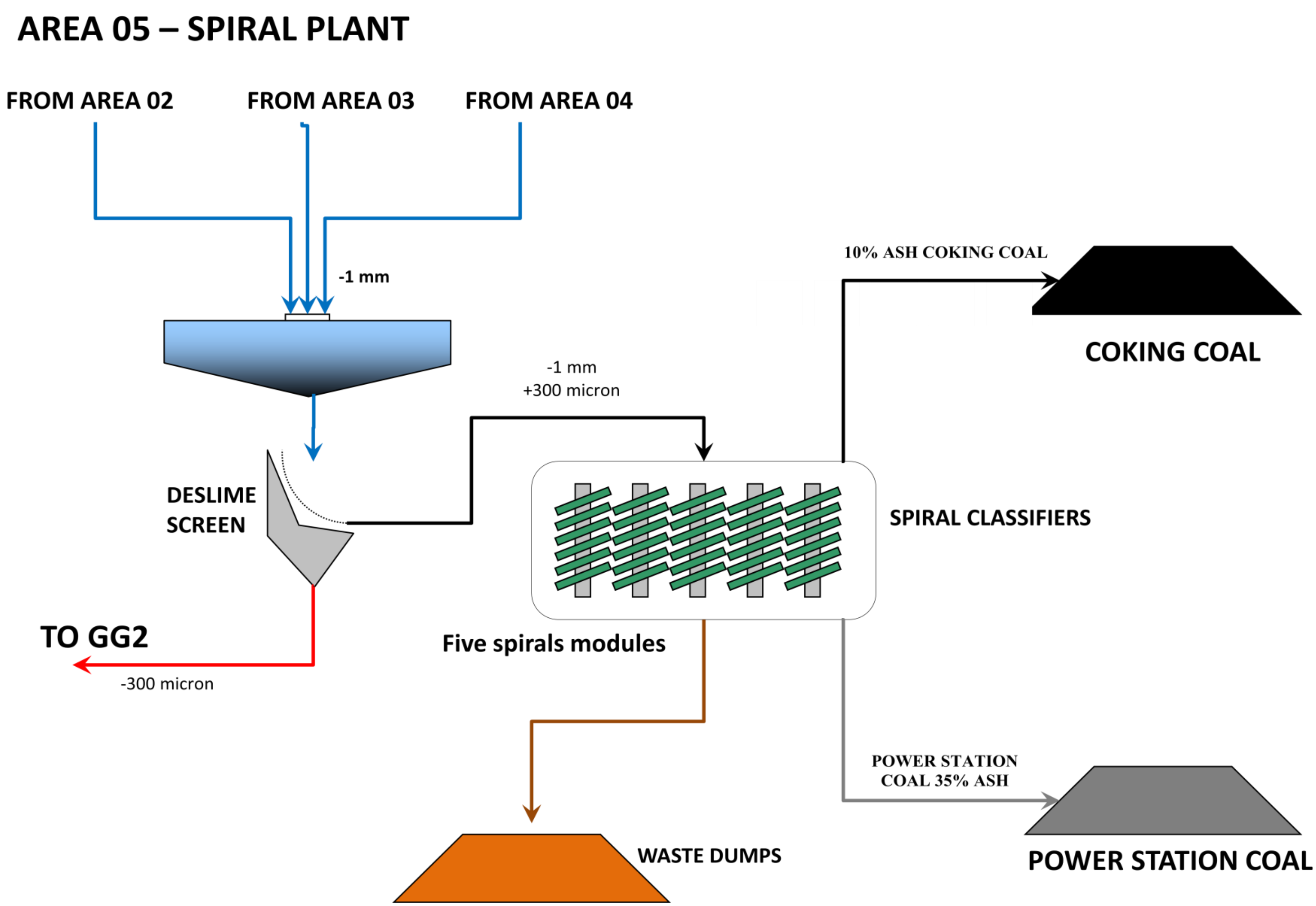
AREA 02 – PRIMARY CYCLONE BENEFICIATION



AREA 03 – TESCA DRUM BENEFICIATION




AREA 04 – SECONDARY CYCLONE BENEFICIATION
RD SOURCES
AREA 04 SILO'S
DMS CYCLONES
+1 mm
-25 mm
LEVEL
METER
-1 mm
Belt Scale
BS
Ash Monitor
TO MODULE 1
TO MODULE 2
TO MODULE 3
TO MODULE 4
TO MODULE 5
10% ASH COKING
COAL
COKING COAL
POWER STATION
COAL 35% ASH
THICKENER


AREA 05 – SPIRAL PLANT
FROM AREA 02
FROM AREA 03
FROM AREA 04
-1 mm
DESLIME SCREEN
-1 mm
+300 micron
TO GG2
-300 micron
Five spirals modules
SPIRAL CLASSIFIERS
10% ASH COKING COAL
COKING COAL
POWER STATION COAL 35% ASH
POWER STATION COAL
WASTE DUMPS

APPENDIX B

STATISTICAL FORMULAS AND THEORY

The variability of a dataset is a useful measure in characterising the different fields within the dataset. The range of a field is a straightforward measure for variability and is highly sensitive to extreme observations. The difference between the maximum value in a field and the minimum value of the same field gives the range of the field (Giudici, 2003).

A more descriptive measure for the dispersion of data relevant to a specific field is the variance of the field distribution. The variance of the different data fields is defined as the degree to which data tend to spread. Variance and the standard deviation (the positive square root of the variance) are measures for the deviations from the average of a specific field (Devore & Farnum, 2005). If the mean of variable x with observations $x_1,\ldots,x_n$ is given by (Kreyszig, 1999):

$$\overline{x} = \frac{1}{n}\sum_{j=1}^{n} x_j \ ,$$

Equation 20

then the variance of the variable is given by

$$s_x^2 = \frac{1}{n-1}\sum_{j=1}^{n}(x_j - \overline{x})^2 \ ,$$

Equation 21

and the standard deviation

$$s_x = \sqrt{s_x^2} \ .$$

Equation 22

The asymmetry of a field is also a descriptive tool used to characterize distribution of the fields. If the median[29] of a data distribution is higher or lower than the data mean value (average), the distribution is said to be skew. For a symmetric distribution, the data median and the average should be equal.

A correlation matrix is a very useful tool in discovering the relationship degree between the different variables contained in a dataset. Two measures for the interrelation between two variables x and y, are the covariance s_{xy} and the correlation coefficient r, given by (Kreyszig, 1999):

$$s_{xy} = \frac{1}{n-1}\sum_{j=1}^{n}\left(x_j - \bar{x}\right)\left(y_j - \bar{y}\right),$$

Equation 23

and,

$$r = \frac{s_{xy}}{s_x s_y} \ .$$

Equation 24

The correlation coefficient is the normalised covariance index. This relative correlation coefficient index indicates the degree of relationship between the two variables. A correlation coefficient value of 1 or -1 corresponds to high correlation or relationship between the two variables. If r takes on a value of zero, the two variables have no relationship with each other.

[29]The median is the value which halves the data distribution. (Giudici, 2003)

APPENDIX C

SCRIPTING LOGIC

The following script is the logic used in the "accumulation calculations" operation layer described in the solution architecture section in chapter 7.

```
if Quality = 1 then
        if firstexecute then
        Cum_Mass_OPT := 0.1
        Cum_Mass_OPT_prev := 0.0
        Cum_Ash_OPT := 0.0
        Cum_Ash_OPT_prev := 0.0
        Cum_SP_Order_prev := 42
        Cum_Tons_RT := 0.0
        Cum_Tons_RT_prev := 0.0
        Cum_Ash_RT := 0.0
        Cum_Ash_RT_prev := 0.0
        CCScale_min := 0.0
        Opt_Mass_min := 0.0
        Target_Ash_prev := 0.0
        Target_Ash_RT_prev := 0.0
        endif



//Cumulative Mass Calculation
        CCScale_min := CCScale/60.0
        Opt_Mass_min := Opt_Mass/60.0
        Cum_Mass_OPT := Cum_Mass_OPT + Opt_Mass_min
        Cum_Tons_RT := Cum_Tons_RT + CCScale_min

        if      Cum_Mass_OPT = 0.0 then
                Cum_Mass_OPT := 0.00001
        endif
        if      Cum_Tons_RT = 0.0 then
                Cum_Tons_RT := 0.00001
        endif
//Cumulative Ash Calculation
        if Ash_per_sec_active = 1 or CCScale_active = 1 then
                if Cum_SP_Order_I = Cum_SP_Order_prev then
                Cum_Ash_OPT := ((Opt_Ash * Opt_Mass_min) +
(Cum_Ash_OPT_prev*Cum_Mass_OPT_prev))/Cum_Mass_OPT
                Cum_Ash_RT := ((      Ash_per_sec * CCScale_min) + (Cum_Ash_RT_prev *
Cum_Tons_RT_prev))/Cum_Tons_RT
                else
                Cum_Ash_OPT := 0.0
                Cum_Mass_OPT := 0.0
                Cum_Tons_RT := 0.0
                Cum_Ash_RT := 0.0
                endif
        elseif Cum_SP_Order_I <> Cum_SP_Order_prev then
                Cum_Ash_OPT := 0.0
                Cum_Mass_OPT := 0.0
                Cum_Tons_RT := 0.0
                Cum_Ash_RT := 0.0
```

```
        else
          Cum_Mass_OPT := field(Cum_Mass_OPT_prev.value,qualitygood,now)
          Cum_Ash_OPT := field(Cum_Ash_OPT_prev.value,qualitygood,now)
          Cum_Tons_RT := field(Cum_Tons_RT_prev.value,qualitygood,now)
          Cum_Ash_RT := field(Cum_Ash_RT_prev.value,qualitygood,now)
        endif

        Cum_Mass_OPT_prev := Cum_Mass_OPT
        Cum_Tons_RT_prev := Cum_Tons_RT
        Cum_SP_Order_prev := Cum_SP_Order_I
        Cum_Ash_OPT_prev := Cum_Ash_OPT
        Cum_Ash_RT_prev := Cum_Ash_RT
        Target_Ash_prev := Target_Ash
        Target_Ash_RT_prev := Target_Ash_RT


//Ash Target Calculations
//Stockpile planned tons
        if      Cum_SP_Order = 43 then
        Target_Mass := 25000

        elseif  Cum_SP_Order = 44 then
        Target_Mass := 25000

        elseif  Cum_SP_Order = 45 then
        Target_Mass := 35000

        elseif  Cum_SP_Order = 46 then
        Target_Mass := 25000

        elseif  Cum_SP_Order = 47 then
        Target_Mass := 25000

        elseif  Cum_SP_Order = 48 then
        Target_Mass := 30000

        elseif  Cum_SP_Order = 49 then
        Target_Mass := 10000

        endif

        if Ash_per_sec_active = 1 or CCScale_active = 1 then
        Target_Ash := ((Target_Mass * Target) - (Cum_Ash_OPT * Cum_Mass_OPT))/(Target_Mass -
Cum_Mass_OPT)
        Target_Ash_RT := ((Target_Mass * Target) - (Cum_Ash_RT * Cum_Tons_RT))/(Target_Mass -
Cum_Tons_RT)
        else
        Target_Ash := field(Target_Ash_prev.value,qualitygood,now)
        Target_Ash_RT := field(Target_Ash_RT_prev.value,qualitygood,now)
        endif

endif
```

APPENDIX D

LIST OF PROCESS VARIABLES

Tag name	Description
Cum_SP_Order	Stockpile number ordered from 1 to 145
	Mass measurements
BeltScale_A04_M1	Belt scale on module 1 in AREA 04
BeltScale_A04_M2	Belt scale on module 2 in AREA 05
BeltScale_A04_M3	Belt scale on module 3 in AREA 06
BeltScale_A04_M4	Belt scale on module 4 in AREA 07
BeltScale_A04_M5	Belt scale on module 5 in AREA 08
CCScale	Belt scale on coking coal product line
PSCScale	Belt scale on power station coal product line
Cum_Tons	Mass accumulation of actual coking coal stockpile
Cum_Mass_OPT	Mass accumulation of optimised coking coal stockpile
Opt_Mass	Optimised coking coal mass flow
Target_Mass	Target accumulated mass per stockpile
	Ash Measurements
RDPresent_A04_M1	RD value as measured by RD source on module 1 in AREA 04
RDPresent_A04_M2	RD value as measured by RD source on module 2 in AREA 04
RDPresent_A04_M3	RD value as measured by RD source on module 3 in AREA 04
RDPresent_A04_M4	RD value as measured by RD source on module 4 in AREA 04
RDPresent_A04_M5	RD value as measured by RD source on module 5 in AREA 04
RDSetpoint_A04_M1	RD set point on module 1 in AREA 04
RDSetpoint_A04_M2	RD set point on module 2 in AREA 04
RDSetpoint_A04_M3	RD set point on module 3 in AREA 04
RDSetpoint_A04_M4	RD set point on module 4 in AREA 04
RDSetpoint_A04_M5	RD set point on module 5 in AREA 04
Ash_per_min	Ash content measured by online ash monitor sampled in one minute intervals

Opt_Ash	Optimised ash content on coking coal product line
RT_Coalscan_Ash	Ash content measured by online ash monitor aggregated in 5 minute samples
RT_Ash_per_5min	Ash content updated by bias in SBS, aggregated in 5 minute samples
HR_Coalscan_ash	Ash content updated by bias in SBS, aggregated in 1 hour samples
Target_Ash	Target ash content calculated in optimisation solution
HR_Ash_bias	Bias calculated from laboratory results, updated hourly
Cum_Ash	Ash accumulation per stockpile from actual process
Cum_Ash_OPT	Ash accumulation per stockpile from optimised results