Process monitoring with economic performance functions: Feasibility assessment for milling circuits

by

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Summary

Milling circuits are operated with a throughput maximisation objective, consistent with achieving a liberation index that promotes optimal mineral recovery in downstream flotation. To meet this objective, this study investigates the feasibility of developing and using economic performance functions to monitor milling circuits. To this end, industrial and simulation cases were studied.

The industrial case study investigated the development of a reliable economic performance function (EPF) that relates controlled variable behaviour to a profit function. To this end, regression models were developed between key controlled variables (mill load, mass pull and particle size) and each of two profit functions, i.e. mineral recovery and financial profit. Subsequently, the development and industrial implementation of a simple and convenient process monitoring tool that assists operators and engineers to make operational decisions based on economic performance predictions was to be assessed. Since fault conditions are unfavourable for profitable operation, the simulation case study assessed the feasibility of fault detection with EPFs. Three faults i.e. increased ore hardness, poor steel ball quality and a load cell drift were simulated and the economic impact of each fault was investigated.

Results for the industrial case study showed difficulty to develop a reliable EPF with industrial data. All but four EPF models were poorly fit and showed an adjusted R-squared value below a selected threshold of 0.6. However, the four identified models were characterised with poor predictions of plant test data. Consequently, the results were not useful for developing a process monitoring tool that could be implemented at the industrial operation.

A number of factors such as data quality, data pre-treatment and the model structure used in the study influenced industrial case study results. To mention a few of these factors, results suggested robust model predictive controller action that rendered data variability insufficient for EPF development purposes. Indications of poorly structured data due to measurement lags, and disturbances in data sequences from faulty data treatment were additional limitations that influenced the quality of results obtained. Moreover, a low sampling frequency for assay composite samples may have contributed to missing in-between shift events.

Simulation case study results showed degraded economic performance at fault inception for two (increased ore hardness and load cell drift) of the simulated faults, to suggest opportunity for fault detection with EPFs. Significance test results pointed to at least one difference in the economic performance indices (EPIs) for

the simulated faults. Although not fully explored in this study, significance test results suggested opportunity for fault prioritisation with the EPI that allows decisions about the corrective action to be made based on the severity of the impact on economic performance.

Since reliable EPF development was the main limitation in this study, a comparative assessment in a different operation with well-structured data is recommended. Fault prioritisation with the EPI may also be an area of interest for future work. However, the shortcomings identified in some of the simplifying assumptions made when deriving the EPI will need to be addressed.

Opsomming

Maalkringe het deurvoermaksimalisering ten doel, gegee dat 'n vrylatingsindeks wat optimale mineraalwinning in stroomafflottering verkry word. Met hierdie doelwit voor oë is hierdie studie gemik daarop om die haalbaarheid van die ontwikkeling en gebruik van ekonomiese prestasiefunksies om 'n maalkring te monitor. Daarom is nywerheids- en simulasiegevalle bestudeer.

Die nywerheidsgevallestudie het die ontwikkeling van 'n betroubare ekonomiese prestasiefunksie (EPF) wat beheerdeveranderlike-gedrag korreleer met 'n winsfunksie ten doel. Daarom is regressiemodelle tussen sleutel beheerdeveranderlikes (meullading, massavloei, en partikelgrootte) en elk van twee winsfunksies, naamlik mineraalherwinning en finansiële wins, ontwikkel. Vervolgens is die ontwikkeling en nywerheidsimplementering van 'n eenvoudige en geskikte prosesmoniteringsinstrument wat operateurs en ingenieurs help om operasionele besluite op grond van voorspellings van ekonomiese prestasie te neem, geassesseer. Aangesien fouttoestande nadelig vir winsgewende werking is, het die simulasiegevallestudie die haalbaarheid van foutspeuring deur middel van EPF's bepaal. Drie foute, naamlik verhoogde ersthardheid, swak staalbalkwaliteit en 'n ladingselafwyking, is gesimuleer en die ekonomiese impak van elke fout is ondersoek.

Die resultate van die nywerheidsgevallestudie het op 'n paar probleme met die ontwikkeling van 'n betroubare EPF met nywerheidsdata gedui. Alle EPF modelle, uitgesluit vier, het swak passing getoon, met 'n aangepaste R-kwadraat waarde van minder as die gekose limiet van 0.6. Die vier geïdentifiseerde modelle is gekenmerk deur die swak voorspelling van aanlegdata. Die resultate was dus nie bruikbaar vir die ontwikkeling van 'n prosesmoniteringsinstrument wat by die nywerheidsproses geïmplementeer kon word nie.

'n Aantal faktore, soos datakwaliteit, datavoorverwerking en die modelstruktuur wat gebruik is, het die resultate van die nywerheidsgeval beïnvloed. Om 'n paar van die faktore te noem, die resultate van die nywerheidsgevallestudie het gedui op robuuste model-voorspellende-beheeraksie, wat dataveranderlikheid onvoldoende vir die doeleindes van EPF-ontwikkeling gemaak het. Aanduidings van swak gestruktureerde data as gevolg van metingsagterstande sowel as steurings in datareekse as gevolg van foutiewe datahantering was verdere beperkinge wat die gehalte van die verkrege resultate beïnvloed het. Daarby kon 'n lae steekproeffrekwensie vir saamgestelde komposisiemonsters daartoe bygedra het dat tussenskofvoorvalle oor die hoof gesien is.

Resultate van die simulasiegevallestudie het verlaagde ekonomiese prestasie met die ontstaan van die fout vir twee die gesimuleerde foute (verhoogde ersthardheid en ’n ladingselafwyking) getoon, wat geleentheid vir foutspeuring met EPF’s voorstel. Betekenistoetsresultate het gedui op ten minste een verskil in die ekonomiese prestasie-indekse (EPI’s) vir die gesimuleerde foute. Alhoewel dit nie ten volle in hierdie studie ondersoek is nie, het betekenistoetsresultate die geleentheid vir foutprioritisering met die EPI voorgestel wat dit moontlik maak om besluite oor die nodige regstellende optrede te neem op grond van die graad van die impak op ekonomiese prestasie.

Aangesien betroubare EPF-ontwikkeling die hoofbeperking in hierdie studie was, word ’n vergelykende assessering in ’n ander proses met goed gestruktureerde data aanbeveel. Foutprioritisering met die EPI kan ook ’n area vir toekomstige navorsing wees. Die tekortkominge wat geïdentifiseer is in sommige van die vereenvoudigende aannames wat met die ontwikkeling van die EPI gemaak is, sal egter steeds aandag moet geniet.

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Nomenclature

Acronym	Description
3E	Platinum (Pt), palladium (Pd), rhodium (Rh)
ANOVA	Analysis of variance
APC	Advanced process control
CFF	Cyclone feed flow
CV	Controlled variable
CL	Centre line
EPA	Economic performance assessment
EPF	Economic performance functions
EPI	Economic performance index
FEA	Financial elements analysis
IPF	Individual performance function
JPF	Joint performance function
KPI	Key performance indicator
MF2	Mill-Float-Mill-Float
MFB	Mill feed balls
MFS	Mill feed solids
MSPM	Multivariate statistical process monitoring
MIMO	Multi-input–multi-output
MPC	Model Predictive Control
MP	Multi-predictors
MR	Mineral recovery
MVC	Minimum variance control
MV	Manipulated variable
MW	Megawatt
NOC	Normal Operating Condition
PAR	Peak Air Recovery
PID	Proportional Integral Derivative
PDF	Probability Density Function
PGM	Platinum Group Metals

PS	Particle size
PVA	Process variables analysis
PM	Process monitoring
ROM	Run-off mine
RSD	Relative standard deviation
SAG	Semi-autogenous grinding
SP	Single-predictor
SPM	Statistical process monitoring
SVOL	Sump volume
LCL	Lower control limit
UCL	Upper control limit
XRDF	X-ray diffraction and fluorescence
Symbol	**Description**
σ	standard deviation
μ	mean
y	controlled variable
ϑ (y)	economic performance function
R	metal sales revenue
F	mill throughput
t	time period (h)
c	conversion factor (oz/g)
C	operating cost (ZAR)
u	unit cost
BP_{adj}	adjusted basket price
B_w	bin width
R^2_{adj}	adjusted R-squared

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CHAPTER 1: INTRODUCTION

Chapter Overview

This chapter introduces the thesis by providing a background to the study and a description of the scope. The research problem is highlighted through a discussion of the motivation and significance of conducting this study. A presentation of the research objectives follows and finally, a thesis layout is provided.

1.1 Introduction

Mineral processing operations are faced with a challenge to consistently achieve satisfactory process economic performance despite fluctuating markets, low-grade deposits with complex mineralogy, increasing operating costs and penalties from stringent environmental regulations. An ongoing implementation of more efficient technologies, strategies on cost minimisation and throughput improvement, as well as timely fault detection and process recovery are some of the commonly applied interventions to meet this challenge (Rule & DeWaal, 2011; Simonsen & Perry, 1999).

To address the challenge highlighted above, this study investigated the feasibility of industrial online primary mill circuit monitoring with a simple and convenient tool developed using an economic performance function (EPF) that related key production and control objectives to profit, as a possible avenue to make operating decisions consistent with satisfactory economic performance. An objective and detailed economic performance evaluation of a platinum group metal (PGM) primary mill circuit at a Concentrator plant provided a reference basis to the investigation. In addition, fault detection with EPFs was investigated in a semi-autogenous grinding (SAG) mill circuit simulation experiment that offered control over fault occurrence and the time window for fault detection.

1.1.1 Process overview of the milling circuits

The milling process reduces ore to a size amenable to efficient mineral recovery in downstream flotation (Matthews & Craig, 2013). Ore feed and steel ball media are charged into a mill for particle size reduction to achieve a liberation index that promotes optimal mineral recovery. Water is added to the mill to form a slurry mixture (also referred to as pulp) with a suitable density for optimal grinding conditions. Ground ore is discharged into a sump, which also acts as a buffer for the circuit where make up water is added to achieve flow and density control. Close control is exercised on the fraction of sub 75 microns product (also referred to as the grind), through classification in a hydrocyclone. Therefore, slurry is pumped from the sump to a hydrocylone where heavy particles report to the underflow stream and are recirculated into the mill for regrinding. Lighter particles report to the overflow stream and are delivered to a froth flotation circuit for mineral recovery. With the aid of reagents, flotation feed is conditioned to modify the surface properties of mineral values and air is introduced into agitated flotation cells to pull/float mineral values into the concentrate at a controlled rate subject to a trade-off between concentrate grade and mineral recovery. Figure 1-1 shows a simplified schematic of a typical milling and flotation circuit.

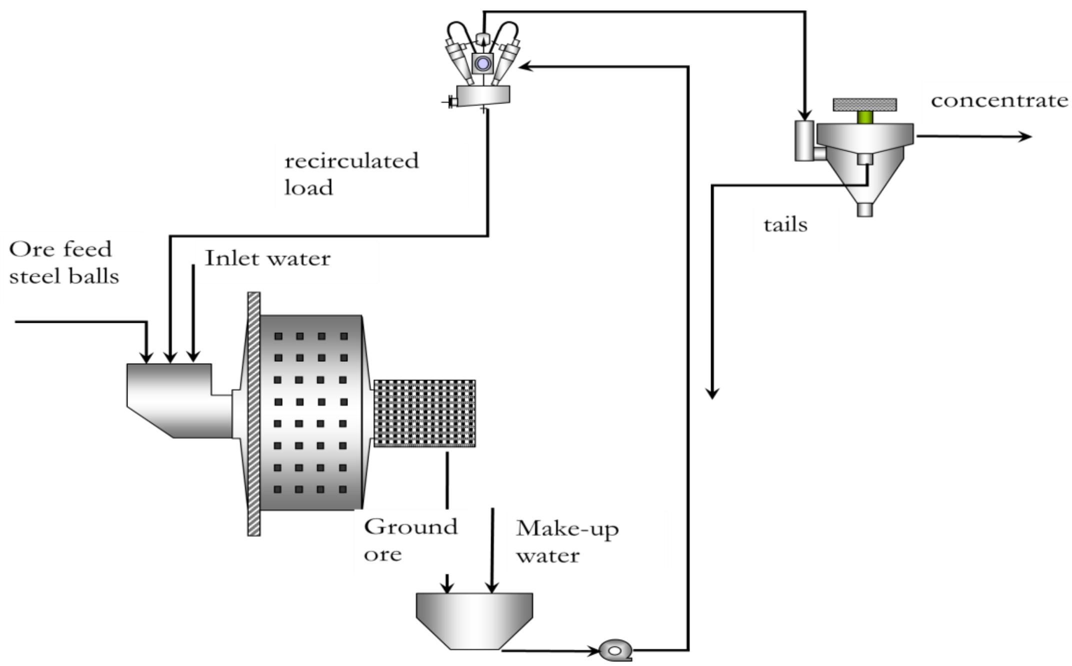


Figure 1-1 Simplified schematic of a milling and flotation circuit.

1.1.2 Overview of the economic significance of milling circuits

Milling is a materials and energy intensive process which drives the cost of mineral processing operations (Powell *et al.*, 2009; Schena *et al.,* 1996). About 40-45% of the total milling costs are attributable to grinding media, and an estimated 40% of mineral processing energy is used up in comminution (Ballantyne & Powell, 2014; Ebadnejad, 2016; Moema *et al.*, 2009). Moreover, the economic performance of downstream flotation efficiency is influenced by the particle size achieved in milling (Hodouin *et al.*, 2001; Valery & Jankovic, 2002). An analysis of recent plant data showed that the rougher flotation circuit typically makes a 65% contribution to the overall mineral value recovered in the concentrator plant. Hence, the primary mill and rougher flotation circuit was an economically significant scope for the investigation.

1.2 Motivation and significance of study

Process monitoring plays a critical role in the delivery of efficient and profitable process operations, through tracking process-related variables to effect control and optimisation of that process. In recent years, the use of simple models to derive product quality from operating conditions, optimise operating conditions and detect faults has become more preferred in industrial operations (Kano & Nakagawa, 2008). Powell & Morrison (2007) recommended the use of these models to monitor comminution processes. Although the simplicity and effectiveness of these models have encouraged widespread use across industries (e.g., chemical and food industry), reliable models are not yet available in the mineral processing industry (Powell & Morrison, 2007; Le Roux *et al*., 2013). The success of these models for process control and monitoring in other industries provides motivation for implementation in the mineral processing industry, where a large number of process variables with complex interactions are monitored and controlled.

The economic significance of milling circuits has led to several economic performance assessment (EPA) studies. However, most of the available EPA studies were conducted for once-off controller performance assessment and amongst these, only a few applied economic performance functions (e.g., Steyn & Sandrock, 2013; Wei & Craig, 2009a; Zhao *et al*., 2009). The reported success of these few studies and a recommendation in Bauer *et al.* (2007) inspired this study, which addressed process performance assessment. Instead of a once-off performance assessment, this study rather investigated the feasibility of continuously monitoring the economic performance of a milling circuit. Furthermore, the EPF used in this study incorporated more controlled variables as well as key revenue and cost metrics associated with operating a milling circuit. The simulation case study followed an approach similar to Wei & Craig (2009a) but addressed an objective to investigate fault detection and prioritisation with EPFs.

The use of simulation and industrial data to develop EPFs is referred to in literature (Bauer *et al*., 2007; Wei & Craig, 2009a). Simulation data was used in most EPA studies, with the exception of Steyn & Sandrock (2013) who used industrial data. The rare opportunity to use industrial data in this study provided some objective insight on the development of reliable EPFs. Consequently, study findings reduced the knowledge gap on reliable economic performance assessment of milling circuits.

According to experts at the industrial operation, no EPFs were developed in the processing history of the primary mill circuit. In addition, no previous research has been conducted on process monitoring with EPFs to the author's best knowledge. The availability of limited information on EPFs has contributed to the low maturity level of demonstrated EPF industrial application and research. As such, the development of EPFs is difficult since they are poorly understood even amongst some industrial experts (Wei & Craig, 2009b). Therefore, this study largely referred to the sequel study by Wei & Craig (2009a,2009b; 2009c) on EPFs and also sought to increase awareness on this promising research area.

1.3 Research objectives

The overall aim of this study is to investigate online process monitoring with EPFs. For the industrial case study, the following objectives were identified:

1. To develop a reliable EPF with industrial primary mill and rougher flotation data;
2. To derive the circuit's benchmark economic performance;
3. To assess the feasibility of industrially implementing an online process monitoring tool for the circuit, using one key controlled variable; and
4. To assess the feasibility of incorporating additional key controlled variables in the process monitoring tool.

For the simulation case study, the overall aim was to investigate the feasibility of fault detection with EPFs. The following objectives were identified:

1. To derive the economic performance of a SAG mill circuit subject to three common industrial faults; and
2. To assess the economic impact of the fault events and subsequently, determine fault detection feasibility with EPFs.

1.4 Research design

A triangulation of qualitative and quantitative approaches were used to explore the two cases studies. The research instruments used for data gathering to achieve the objectives of this study included a literature survey, site survey at the industrial Concentrator plant and simulation experiments.

1.5 Thesis outline

This thesis progresses as follows:

Chapter 2 presents a literature review on assessing the economic performance of milling circuits. Chapter 3 follows with a literature discussion on the significance of fault detection in process monitoring. Model and data based approaches are distinguished, and common faults in milling circuits are identified. In Chapter 4, site survey findings on the process operation, control and economics of an industrial primary mill circuit are presented. Research methodology steps for the industrial and simulation case studies are proposed in Chapter 5. Chapter 6 presents the industrial case study results and discusses findings thereof. Similarly, Chapter 7 presents the results and discussion for the simulation case study. This thesis concludes with Chapter 8 wherein the key findings of this study are summarized. The final conclusions to the study are made, and recommendations for future work are presented.

CHAPTER 2: ECONOMIC PERFORMANCE ASSESSMENT OF MILLING CIRCUITS

Chapter Overview

This chapter reviews literature on assessing the economic performance of milling circuits. The overall aim is to provide insight on two objectives for this study i.e., EPF development with industrial data and the derivation of an economic performance index. To this end, factors that significantly influence economic performance are identified and the critical role of process control in delivering economic benefits is discussed using demonstrated studies. Economic performance functions are introduced and their significance, development, and application are highlighted. Methodology steps on economic performance assessment are presented, and this chapter concludes with techniques for industrial data treatment prior to EPF development. By the end of this chapter, relevant strategies for developing EPFs in this study are identified as well as a procedure to derive the primary mill circuit's economic performance.

2.1 Factors influencing economic performance

The economic performance of milling circuits is assessed across a number of objectives that include profitability, efficiency, product variability and throughput (Ellis *et al.,* 2014). A holistic consideration of these key objectives is necessary for representative economic performance assessment. Commonly, cost minimisation or revenue maximisation strategies are used to achieve maximum profit (Simonsen & Perry, 1999). Milling processes significantly contribute towards the overall mineral processing operating cost structure due to energy, grinding media, and costs for replacing mill liners. For flotation processes, reagent consumption is a major cost (Wills & Napier-Munn, 2006). Energy consumption accounts for about 50% of the total comminution costs and in addition, grinding media constitutes of up to 40–45% and liner wear 5-10% (Moema *et al.*, 2009; Radziszewski, 2013). Therefore, the reduction of utility and consumable quantities is one commonly implemented cost minimisation strategy. On the other hand, increased throughput rates and consistent attainment of target product quality achieve profit maximisation (Matthews & Craig, 2013). According to Cavender (2001), consistent compliance with operating conditions and standards, optimisation of operating practices through continuous improvement research work, and equipment maintenance or upgrades contribute towards improved economic performance. However, not all of these strategies are easy to implement without applying process control to achieve economic efficiency. Therefore, process control is used in virtually all milling circuit operations to achieve target operating and consequently, economic objectives (King, 2001).

The highly dynamic nature of milling circuit operations makes process control necessary in order to simultaneously maintain the large number of controlled variables at their set points (Jakhu, 1998). Additional benefits such as process variability reduction, increased efficiency, safe operating conditions are achieved (Contreras-Dordelly & Marlin, 2000).

The next section introduces a process control hierarchy as a basis for discussing the economic benefits derived with process control. This discussion leads to a review of some relevant economic performance assessment (EPA) studies.

2.2 Process control assessment

2.2.1 Process control hierarchy

Different functional levels of process control systems contribute to the overall control performance and consequently, process performance (Zhou *et al.*, 2011). Shean & Cilliers (2011) distinguished a four interconnected multi-level process control hierarchy shown in Figure 2-1.

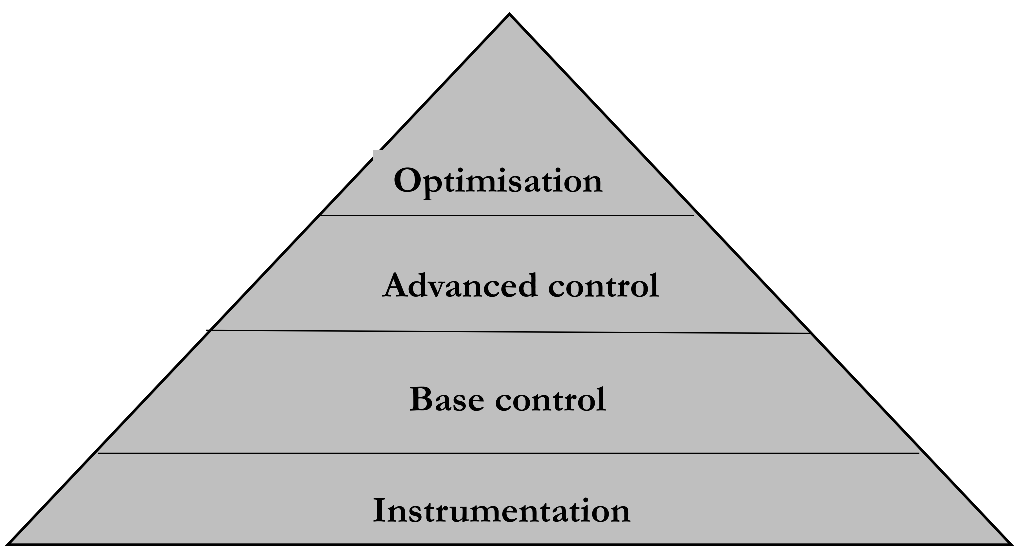


Figure 2-1: Process control hierarchy (Redrawn from Laurila *et al.,* 2002)

The effectiveness of each level is a pre-requisite for successful higher-level operation. However, lower levels may still operate even when higher levels do not. Each process control level is discussed below:

2.2.1.1 Instrumentation

At the lowest level in the process control hierarchy, instrumentation provides process observations for process monitoring, control and optimisation (Shean & Cilliers, 2011). Regular instrumentation maintenance ensures measurement reliability and enables process regulation within an acceptable operating window.

2.2.1.2 Base control

Controllers implemented at base level transfer the variability introduced by disturbance variables away from controlled variables to manipulated variables and hence, achieve stable operation (Oosthuizen *et al.*, 2004). This level uses interlocks and sequences to ensure safe and reliable operation (Fiske, 2006). Milling circuits predominantly implement proportional-integral-derivative (PID) controllers for base control (Edwards *et al.*, 2002).

2.2.1.3 Advanced control

Advanced control improves the economic performance of a process through stabilisation, to achieve the desirable operating window to enable process optimisation (Almond *et al.*, 2012; Smith & Corripio, 1997). As pointed out by process stabilisation not only. Milling circuits commonly implement fuzzy logic, rule-based expert system, and model predictive control for advanced control (Wei & Craig, 2009b).

2.2.1.4 Optimisation control

Optimisation control is only achievable when underlying base control has established stable operation (Laurila *et al.,* 2002). This level typically uses mathematical modelling and simulation to determine set points for optimum process performance, based on maximizing or minimizing an objective function (Valenta & Mapheto, 2011). A trade-off between mill throughput and mineral recovery is dynamically optimised at this level to maximise economic efficiency (Barker, 1989).

Optimal process performance is only maintained when process disturbances are compensated for and process variability is reduced (Herbst *et al.*, 1988). The economic benefits derived from variability reduction are discussed in the next section.

2.2.2 Economic benefits of process control

Process variability in milling circuits is induced by several factors such as changes in feed ore characteristics (hardness, grade, particle size), ore feed rate and quality, mill sump level, mill load, product particle size and mill discharge viscosity (Hodouin *et al.*, 2001; Wei & Craig, 2009b). Furthermore, non-uniform feed ore mineralogy, grind size, flotation feed flow and pulp density as well as spillage due to malfunctioning ancillary equipment, are sources of process variability in flotation circuits (Villeneuve *et al.*, 1995). The frequency and severity of these disturbances significantly influence milling circuit performance to produce off-specification and consistently variable product quality (Brisk, 2004; Oakland, 2003).

A reduction in process variability is linked to the economic performance of that process. Benefit potentials have been realised through either simultaneous variability reduction of controlled variables (CVs) and a shift in the mean operating point towards the set point, or from tuning constraints (Xu *et.al.*, 2007). However, a violation of controlled variable constraints negatively affects the economic performance of the process. Conversely, a loss is incurred for operating away from the set point (Bauer *et al.*, 2007; Craig & Koch, 2003; Oosthuizen *et al.*, 2004). Figure 2-2 shows profit improvement realised from operating closer to the set point after a reduction in process variability.

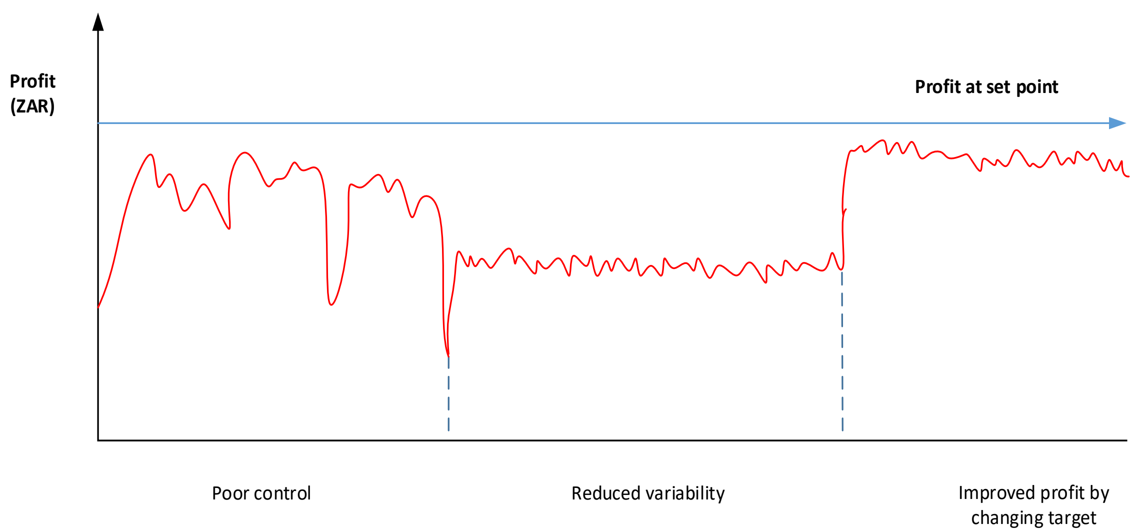


Figure 2-2: Economic benefits of variability reduction **(**Adapted from White, 2003)

Several studies have estimated the benefits associated with variability reduction for milling and flotation circuits. A 1% recovery gain was achieved from stabilizing flotation cell level around the optimum level (Schubert *et al.*, 1995). Increased throughput, reduction in throughput and mill load variability, improved energy utilisation, attainment of target product particle size, and recovery gain were also reported as major benefits from variability reduction (Bauer & Craig, 2008; Bouffard, 2015; Gupta *et al.*,2013; Wei & Craig, 2009b). Brisk (2004) identified safer operation, minimized environmental impact, manufacturing sustainability, as well as improved efficiency and quality and agility gains as additional key benefits. However, these benefits were difficult to quantify monetarily due to subjective measures with safety or legal considerations.

The economic significance of reduced variability has resulted in a number of assessment studies that address several controller performance objectives. Some studies assessed the economic impact of implementing advanced control either before or after installation (e.g. Bauer *et al.*, 2007); monitored current controller performance (e.g. Rato & Reis, 2010); compared controllers to identify a better performing one (e.g. Craig & Henning, 2000; Wei & Craig, 2009a); and to optimise processes (e.g. Marlin *et al.*, 1991; Steyn & Sandrock, 2013; Zhao *et al.*, 2009). Despite the numerous studies on controller performance assessment, only a few (e.g., Wei & Craig, 2009a; Zhao *et al.*, 2009) focused on deriving the economic performance monetarily.

Similar concepts from these EPA studies were applicable to this study. The next section discusses key factors associated with economic performance assessment.

2.3 Background to economic performance assessment

The most important step to any EPA is a prior consideration of the objectivity and accuracy of a criterion upon which performance is to be evaluated (Jämsä-Jounela *et al.*, 2003). Therefore, the first step is to identify a performance index that represents the assessment objective. The selected index must have a satisfactory confidence level that is verifiable with plant data. Hence, selection methods must be realistic and achievable under specific physical constraints (Jämsä-Jounela *et al.*, 2003; Xia & Howell, 2003). For example, Wei & Craig (2009a) addressed a common milling circuit objective i.e., to achieve the target particle size from which a profitable mineral recovery can be realised to evaluate the profit realised from implementing a new controller. Their study results were also industrially realistic.

An appropriate benchmark is selected after a performance index has been identified. Some performance assessment studies have used minimum variance control (MVC) and the historical-data benchmarks (e.g. Bauer *et al.*, 2007; Jelali, 2006; Rato & Reis, 2010; Zhao *et al.*, 2011). MVC benchmarks are derived from a performance index which compares the minimum variance achievable to actual controller variance, as shown in Equation 2-1(Harris *et al.*, 1989).

$$\eta^{MVC} = 1 - \frac{\sigma_{MVC}^2}{\sigma_{ACT}^2} \qquad \textbf{2-1}$$

Where σ^2_{MVC} is the minimum achievable variance

σ^2_{ACT} is the actual controller variance

Preference for the MVC benchmark is associated with benefits realised from operating a process within profitable controlled variable constraints and how variability reduction can be directly related to profit improvement (Brisk, 2004). Furthermore, this benchmark is computationally simple and routine operating data are used without the need for additional experiments (Muske & Finegan, 2001). However, it is more relevant for cases in which performance on controller disturbance rejection is considered (Qin & Yu, 2007).

Although time correlations typically influence a process output, a linear time-invariant transfer functions and additive disturbances are assumed for the process whenever the MVC benchmark is used (Jelali, 2010). Furthermore, some researchers (e.g. Huang *et al.*, 1997; Zhao *et al.*, 2009), have raised concern over its robustness and argue that it is unrealistic relative to other benchmarks since it suggests excessive controller action. The unavailability of perfect disturbance models is yet another reliability challenge faced with this benchmark as a disturbance model mismatch produces inaccurate performance (Eriksson & Isaksson, 1994; Hugo, 2001). Due to these limitations, the MVC benchmark is rarely implemented in industry. Nonetheless, most researchers (e.g. Huang *et al.*, 1997; Hugo, 2001; Hoo *et al.*, 2003; Stanfelj & Marlin, 1993; Yuan & Lennox, 2009) widely acknowledged its useful application as a theoretical approach in most controller performance assessment studies.

Bauer *et al.* (2007) demonstrated the MVC benchmark in a justification study for implementing a new industrial controller. In the study, historical data was used to estimate base case performance while improved performance was derived from simulation data. Subsequently, they derived an economic performance index (EPI) as a function of the standard deviation (Equation 2-2). This EPI derivation method is validated in a number of studies (Bauer & Craig, 2008; Latour *et al.,*1986; Oosthuizen *et al.*, 2004; cited by Wei & Craig, 2009a).

$$\text{EPI} = \int_{-\infty}^{\infty} \vartheta(y) f(y, \sigma, \mu) dy \qquad \textbf{2-2}$$

where ϑ - economic performance function

f - frequency distribution or probability density function (PDF) of the time series of a controlled variable *y*, which was assumed to have a Gaussian distribution

σ - standard deviation of the controlled variable, y

μ - mean of the controlled variable, y

Consequently, a decision to implement the new controller was reached based on an evaluation of the potential profit improvement (determined from the MVC benchmark) against the estimated maximum achievable profit derived with Equation 2-2. However, the study did not consider installation costs although doing so would have provided an insightful cost-benefit analysis.

A user-specified historical performance benchmark compares routine operating data that is representative of past satisfactory performance against current performance (Brisk, 2004). However, an expert assessment of comprehensive plant data over a period that is influenced by the objectives to be achieved is required (Patwardhan *et al.*,2002). Commonly, this benchmark is obtained from a stable operation during which there were no unusual conditions such as equipment outages or an out-of-control state (Latour *et al.*, 1986; Nel *et al.*, 2004).

Although the historical-data benchmark is convenient, easy to apply and interpret, it has some shortcomings. Interpretations of previously good performance may differ even with expert assessments, thus it is rather subjective since a standard performance basis is difficult to establish (Patwardhan *et al.*, 2002). Furthermore, the lack of a theoretical minimum that can be used irrespective of the process or controller is an additional concern relating to its subjectivity. Consequently, the cause of performance degradation cannot be confidently assigned as it is not immediately obvious whether performance changes are attributable to the controller's core functions or to changes in process disturbances. As a result, very few studies (e.g., Rato & Reis, 2010) demonstrated this benchmark. The historical-data benchmark is a relevant alternative for industrial use, and is considered to be less complex relative to the MVC benchmark (Shah *et al.*, 2005; Rato & Reis, 2010).

A study by Rato & Reis (2010) investigated the suitability of a historical-data benchmark to monitor controller performance and detect degradation due to factors external to the process control system. The benchmark was derived from a reference dataset generated in a distinct time period where satisfactory controller performance was achieved. The performance thereof was constantly assessed against current performance using a fixed window size so that degradation in controller performance could be identified.

The next section gives an overview of the significance, development, and application of EPFs. Subsequently, two case studies where EPFs were applied to economic performance are discussed.

2.4 Economic performance functions

Bauer *et al.* (2007) discussed the quadratic, linear and performance function types in terms of their functional forms. These types have been referred to by Steyn & Sandrock (2013); Wei & Craig (2009a; 2009b; 2009c); Xu *et al.* (2011); Yin *et al.* (2015) and Zhao *et al.* (2011). The section below discusses each type with a relevant example for milling and flotation operations.

2.4.1 Quadratic performance function

The quadratic performance function shown in Figure 2-3, depicts maximum benefit (ϑ_m) when a controlled variable lies at an optimal set point (x_m). This benefit diminishes when a controlled variable deviates from the optimal set point (x_m) until beyond the points, $x_m \pm x_1$, where the profit is zero. A common example of the quadratic performance function is the mill product particle-size and flotation mineral recovery relationship. Maximum mineral recovery and hence maximum benefit is realised at the optimal grind. The mineral recovery decreases with either finer or coarser grind (Bauer *et al.*, 2007).

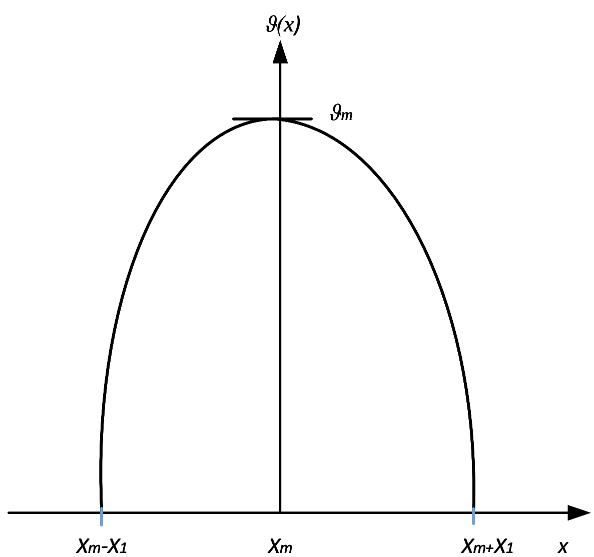


Figure 2-3: Quadratic performance function (Redrawn from Bauer *et al.*, 2007)

2.4.2 Linear performance function

The performance function shown in Figure 2-4 increases linearly from a point x_1, to an operating constraint x_2, which when exceeded results in zero profit.

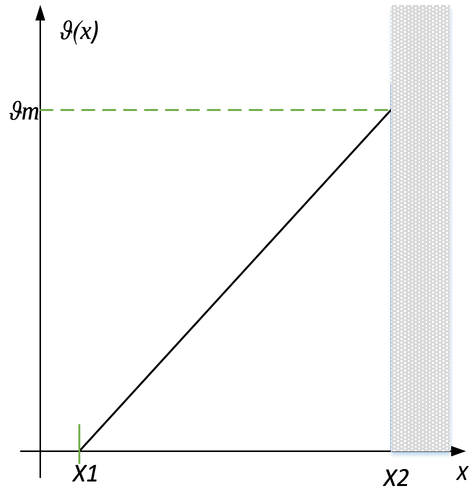


Figure 2-4 : Linear performance function (Redrawn from Bauer *et al.,* 2007)

2.4.3 Clifftent performance function

A clifftent performance function consists of two linear constrained performance functions which increase and decrease linearly, with a maximum economic benefit (ϑ_m) at the operating constraint, i.e. $\vartheta_{cliff}(x) = \vartheta_1(x) + \vartheta_2(x)$, where x_1 and x_3 are zero profit thresholds and x_2 is the point at which the maximum economic benefit, ϑ_m, is achieved for the zero variance. Figure 2-5 illustrates the clifftent performance function.

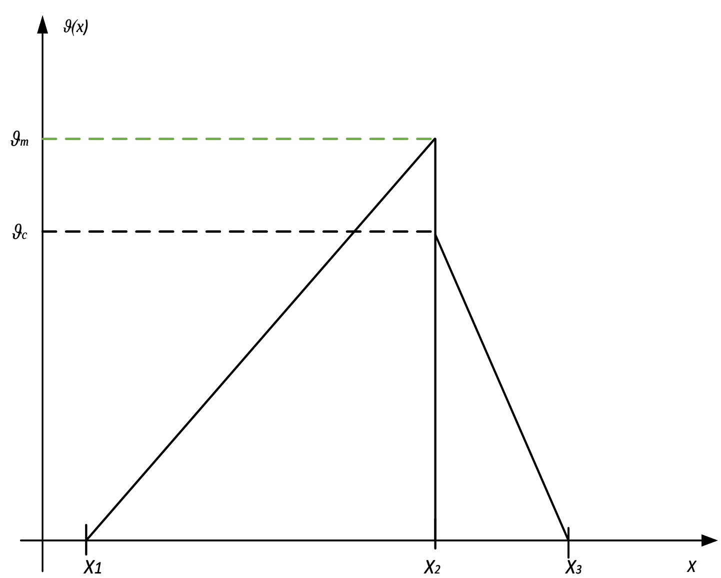


Figure 2-5 Clifftent function (Redrawn from Bauer *et al.*, 2007)

The mill load is operated with tight control near an operating constraint to maximise throughput and hence, maximise economic benefit. When upper and lower limits are exceeded, the economic benefit reduces albeit to different extents to resembles a clifftent performance function (Wei & Craig, 2009a). The mass pull-concentrate grade relationship in the flotation circuit, also characterizes this function. When mass pull continuously increases beyond a profitable constraint, flotation selectivity diminishes and gangue material begins to float. Consequently, the concentrate grade decreases until there is no profit.

As explained with the three performance function types, milling and flotation circuit controlled variables produce different economic consequences due to their behaviour with respect to operating limits and implemented control strategies. Clearly, a reduction in the variability of controlled variables can translate to improved economic performance.

2.5 Significance and application of economic performance functions

Economic performance functions (EPFs) relate the dynamic behaviour of a controlled variable to money. As such, they have a wide application in processes where controlled variables are controlled for economic reasons and therefore, underlie almost every process. EPFs vary from process to process such that generic EPFs are difficult to obtain even when the same process in different operations is considered. This occurrence is due to different performance measures and operating strategies implemented across operations. Furthermore, EPFs change within the same process and need to be constantly reviewed (Wei & Craig, 2009a; 2009c).

EPFs are only applicable to process variables with an operating constraint. Therefore, benefits derived from improved operating safety and reliability are not incorporated in economic performance functions (Bauer & Craig, 2008). Furthermore, the control technology used in a process does not significantly influence EPFs. Instead, factors such as process dynamics, process economics, operational specifications, and market conditions are more relevant (Craig & Henning, 2000; Bauer *et al.*, 2007; Wei & Craig, 2009a).

Although EPFs appear to be a significant tool for economic performance assessment, they are poorly understood. This was observed from the results of a web-based survey conducted for mineral processing experts in operations across the world. The experts who included process engineers, plant managers and metallurgists, as well as mill and metallurgical superintendents could not adequately specify the relationships that best described the economic behaviour of selected controlled variables. The poor understanding of EPFs may be attributed to limited available information. For example, prior to the contribution by Wei &

Craig (2009b), there had been no clearly established methodology on developing EPFs. In addition, this thesis also sought to address these limitations and extend the existing methodology to address the scope considered in this study.

2.6 Development of economic performance functions

Economic performance functions are difficult to develop and therefore, rely heavily on assumptions to simplify the highly complex economic relations in most processes. Thus, knowledge gaps are overcome since complete knowledge on the process is often unavailable (Bauer & Craig, 2008). Credible performance estimates are achieved through careful consideration of the assumptions made, as well as a judicious consideration of the unique performance objectives for the process (Craig & Henning, 2000; Wei & Craig, 2009b). As an example, most EPA studies (e.g., Bauer & Craig, 2008; Wei & Craig, 2009a; Matthews & Craig, 2013) treated a process product as the final sellable product to enable the derivation of a monetary value for economic performance. An assumption to neglect small economic consequences is made in most studies (Steyn & Sandrock, 2013; Wei & Craig,2009a; Zhou & Forbes, 2003), and only key factors are identified (Griesel, 2008).

The development of reliable EPFs requires an in-depth understanding of the process operation, process control and process economics which is not obvious from process data (Bauer & Craig, 2008). Therefore, each of these three factors must be critically analysed. Production objectives and consequently, performance metrics must be established for the process operation. Information on the process description, utilities, and consumables used in the process for which EPFs are to be developed, is also necessary. Process control objectives must be well understood and aspects that include typical process disturbances, selection criteria of controlled and manipulated variables, controlled variable operating limits, and the compensative action required when operating limits are violated. An understanding of controlled variable interactions is also critical. Finally, knowledge of the resultant economic impact when controlled variable specifications are violated is necessary to understand process economics. Hence, controlled variables with the largest economic impact must be considered since not all controlled variables are directly controlled for economic reasons. Similarly, not all operating costs are very significant (Bauer *et al.*, 2007; Wei & Craig, 2009a; 2009b). Clearly, in order to develop a reliable EPF for this study, a judicious selection of key controlled variables must be performed, as well as a careful assessment of operating cost distributions for the primary mill circuit.

EPFs can be developed by survey research, literature survey, plant tests, and from expert knowledge (Bauer & Craig, 2008). Experienced process engineers possess an understanding of the economic impact of important controlled variables (Bauer *et al.*, 2007). Therefore, Wei & Craig (2009b) conducted a web-based survey research in which experts were consulted to gain an in-depth process understanding of milling circuits. In another study, Wei & Craig (2009a) applied a literature survey to develop EPFs for milling circuit variables. Plant tests are rarely conducted as they are extremely time-consuming and may require the costly interruption of normal operation. Despite this limitation, Steyn & Sandrock (2013) conducted a study using plant tests.

Historical data from industrial operation is a more acceptable alternative to plant tests. Although organisational data is confidential, better process understanding is gained from empirically developing EPFs as was done in this study. Moreover, degrading process performance is easy to detect with knowledge of past performance. Zhou & Forbes (2003) recommend an empirical analysis of product value and production costs for EPF development, as done in this study.

Data from laboratory experiments and simulation studies are also suitable for EPF development (Craig et al., 1992). For example, Edwards & Vien (1999) derived a quadratic performance function between the particle size and mineral recovery using laboratory grind and float experiments. Runge *et al.* (2007) also validated the quadratic relationship between product particle size and mineral recovery with three different flotation models that related flotation feed particle size to flotation circuit performance. In addition, some simulation studies (e.g. Bauer *et al.*, 2007; Craig & Henning, 2000; Wei & Craig, 2009a; Zhao *et al.*, 2009) have been used for EPF development.

With a good experimental design, the simulation approach is more accurate and simulation experiments can be easily replicated (Craig & Koch, 2003). The main challenge however, is the difficulty in predicting industrial performance with simulation models due to either model uncertainties or the numerous disturbances that occur in industrial mineral processing operations (Contreras-Dordelly & Marlin, 2000; Sosa-Blanco *et al.*, 2000). In conclusion, combined approaches to EPF development are more effective as demonstrated by Wei & Craig (2009a,2009b; 2009c).

2.7 Derivation of the economic performance index

An economic performance index (EPI) is estimated for a specified operating period based on the variability of a controlled variable around a set point (Bauer & Craig, 2008; Jelali, 2006; Wei & Craig, 2009a). It is a function of controlled variable set point and standard deviation of the time series. Therefore, the time correlation does not matter as two different control conditions with the same probability density function

(PDF) but different autocorrelation functions will produce the same economic performance index (Jelali, 2010; Gupta *et al.*, 2013).

Process economic performance is influenced by process variance, product quality, energy and material consumption (Bezergianni & Georgakis, 2003). Therefore, an EPI that links a reduction in controlled variability, revenue and production costs is more useful (Bauer & Craig, 2008; Gupta *et al.*, 2013; Hodouin, 2011). This is especially important for milling circuit operations, where trade-offs between mill throughput, concentrate grade, and mineral recovery are made. Furthermore, where production costs arising from electricity and grinding media consumption are significant (Votteler & Brent, 2017; Wills & Napier-Munn, 2006).

Milling circuit variables are known to be strongly dependent on each other (Wills & Napier-Munn, 2006). Dependencies exist between particle size -mill load, particle size-sump slurry discharge density, and mill load-mill power (Wei & Craig, 2009c). A joint performance function (JPF) is developed for such cases to account for resultant economic consequences, using a ratio of contribution assigned between each controlled variable based on dependence strength.

Wei and Craig (2009b) proposed the following methodology steps (Figure 2-6) to determine the EPI using economic performance functions.

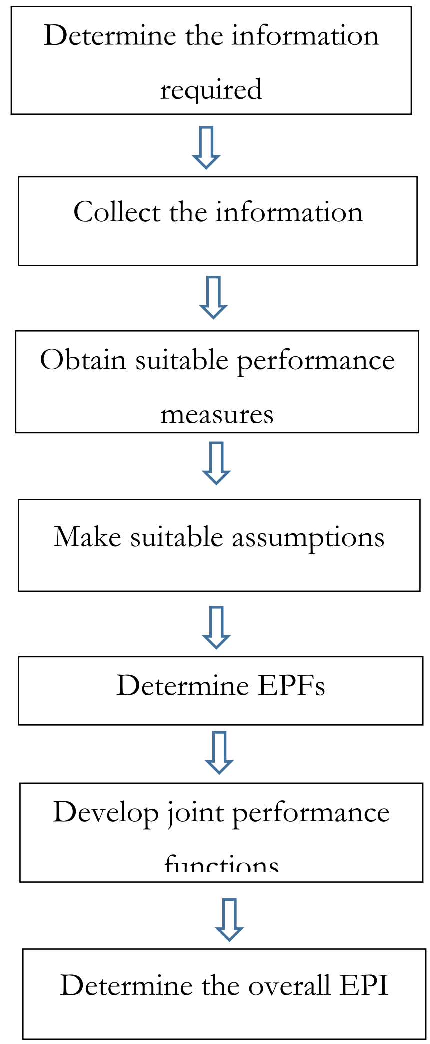


Figure 2-6: Derivation of an EPI

In the next section, two EPA case studies conducted within milling circuits are reviewed.

2.8 Economic performance assessment case studies

Most EPA studies conducted for milling circuits use the crucial link between particle size and mineral recovery to relate the performance of milling and flotation circuits. An independent assessment of milling and flotation circuit performances is complicated (Craig & Henning, 2000). The major drawback for flotation circuit EPA studies has been the difficulty to distinguish between flotation cell and feed properties due to strong stream interactions and this limitation is addressed by linking milling and flotation circuits (Runge *et al.*, 2013). Although this is the best alternative, the lack of in-depth examination of the flotation circuit is still a key shortcoming. Therefore, the common practice has been to derive milling circuit economic performance with particle size, which is a measure of milling product quality and a major determinant of downstream mineral recovery efficiency (Bauer & Craig, 2008; Matthews & Craig, 2013).

2.8.1 Case study of Steyn and Sandrock

Steyn & Sandrock (2013) assessed the economic benefit achieved by stabilising an industrial autogenous PGM primary mill at its optimum power utilisation with a model predictive controller. A linear primary mill and final grind relationship was modelled and subsequently, a relationship between the final grind and mineral recovery was developed based on an assumption of perfect flotation. Fixed costs were assumed to remain constant and mill liner cost was beyond the scope of their study. Therefore, the study only considered the cost related to energy consumption.

Steyn & Sandrock (2013) derived the EPI as the financial profit determined between revenue (Equation 2-3) and cost (Equation 2-4) over the period of assessment.

$$R = BP \times F \times HG \times PR \times t \times c \tag{2-3}$$

where R – metal sales revenue

BP - PGM mineral basket price (ZAR/oz)

F - throughput rate (t/h)

HG - head grade (g/t)

PR - potential recovery (%)

t - time period (h)

c - conversion factor (oz/g)

The cost was determined as below:

$$C = u \times P \times t \tag{2-4}$$

where C - cost (ZAR)

u - unit cost of power (ZAR/kWh)

P - power consumed (kW)

t - time period (h)

There was some difficulty to develop a model between the primary and final grind so as to infer the final mineral recovery. This pointed to challenges associated with developing models with real plant data, and without *a priori* knowledge of the relationship between variables. Although using the final grind was more appropriate for the assessment, the development of a reliable model was likely limited by complex interactions between process streams because of recirculating streams. Moreover, different objectives govern primary and downstream milling such that primary mills are typically tonnage mills with an operating objective to maximize throughput. On the other hand, secondary or regrind mills rather focus on achieving the target grind (Giddy, 1988; Moys *et al.*, 1996). Despite this major limitation, the economic performance assessment by Steyn & Sandrock (2013) represented key metrics associated with milling circuit operation..

2.8.2 Case study of Wei and Craig

Wei & Craig (2009a) assessed the economic performance of two controllers in a simulated run-off mine (ROM) milling circuit. The assessment determined a better performing controller based on the rejection of typical milling circuit disturbances, to achieve target particle size. Subsequently, the mineral recovery was predicted with *a-priori* particle size-mineral recovery performance function.

The following assumptions were made in the EPA study:

1. the milling product was flotation circuit feed;
2. the head grade, throughput rate, and mineral price remained constant;
3. the flotation product was the final sellable product; and
4. milling circuit and downstream flotation operating costs remained constant with slightly better or worse grinding.

The EPA relevantly considered major installation costs to give a detailed cost-benefit analysis of implementing a new controller. However, some issues may need further investigation. A well-performing controller takes action to restore controlled variables within an acceptable operating window when a disturbance causes deviation. Hence, the large step disturbance applied to ore hardness and rock fraction in the simulation experiments likely increased the amount of electricity required to achieve target particle size since mill power draw typically increases with ore hardness and rock fraction (Coetzee *et al.,* 2008; Rajagopal & Iwasaki, 1992). Furthermore, an increase in ore hardness and rock fraction results in increased ore retention time, to become throughput limiting (Wills & Napier-Munn, 2006). Therefore, assumptions of fixed mill throughput rate and electricity consumption are only justifiable on the basis that economic consequences arising from changes in throughput rate and mill power draw were not significant for comparing controller performance.

Since it is particularly challenging to account for every factor contributing to the economic performance of a milling circuit due to the highly complex economic relations, the role of simplifying assumptions is well acknowledged. However, a shortcoming was identified in one of the assumptions made by Wei & Craig (2009a). Flotation product was assumed to be the final sellable product, however, the revenue generated was not appropriately adjusted to account for downstream beneficiation as done in Matthews & Craig (2013).

The two case studies demonstrate that economic performance functions provide a powerful tool for evaluating the economic benefit of process control. However, an evaluation of economic performance is impossible without simplifying assumptions. A Gaussian probability density function was assumed for the data used in both case studies. Goodness of fit tests and visual plots may be used to test this assumption (Hair *et al.,* 2010). The Kolmogorov-Smirnov, Shapiro-Wilk, Cramer-vom Mises and the Anderson-Darling are four commonly used tests (Royston & Matthews, 1991). Alternatively, normal probability and quantile plots may be used. The probability plot shows the cumulative probability of a variable against the normal distribution cumulative probability, and the quantile plot shows data set quantiles. Data are plotted against a theoretical linear normal distribution and any departure from the straight line corresponds to departure from normality. Quantile plots are more easily interpreted for large sample sizes (Ghasemi & Zahediasl, 2012). The inclusion of key revenue and cost metrics was common in both studies i.e., Steyn & Sandrock (2013) included throughput and mineral recovery for the revenue, and electricity as a cost element. Wei & Craig (2009a) considered mineral recovery and controller installation costs. Although the EPA studies were conducted once off, the success thereof may point to opportunity for implementing EPFs in process monitoring.

Industrial data for EPF development must be reliable because any inaccuracies lead to substantial bias in estimating economic performance. The next section discusses techniques for handling faulty data to improve the quality of empirical EPFs with industrial data.

2.9 Faulty data handling techniques

Historical process data contain faulty data, which manifests as incomplete data with missing values, anomalous data with impossible values and noisy data such as outliers. Accurate estimation of economic performance becomes difficult when insufficient, incomplete and/or unreliable process measurements are used (Ma *et al.*, 2010). Therefore, appropriate data handling techniques are applied.

2.9.1 Incomplete data with missing values

Valid observations for one or more variables may be unavailable for analysis. Valuable information is lost when large amounts of data are missing and consequently, EPF reliability is threatened (Kang, 2013). EPFs estimated from data with a large number of missing values may be biased, particularly if the values are systematically different from available data. To reduce bias and achieve reliable conclusions, cases with missing data are handled with appropriate methods.

Missing data constituting less than 15% of individual variables is ignored except when missing data occurs in a non-random fashion. Otherwise, case reweighting or multiple imputations may be considered if a large percentage of cases are missing data (Hair *et al.*, 2010). When a strategy to use complete vectors is considered, observations in other variables that correspond to the missing data are deleted. This is necessary when there is a systematic association between variable observations that directly affects the analysis (Langkamp *et al.,* 2010).

2.9.2 Outlier detection

Outliers are unusual observations that are considerably different from the general data trend (Chandola, 2009; Rahman *et al.,* 2012). In this study, outliers can drastically influence the reliability of EPF predictions and the process monitoring tool's benchmark performance. Outlier sources in industrial data include transmission or transcription errors. In addition, incorrect manual data entry of laboratory assays or measurement errors from undetected sensor failures may occur. Outliers must be judiciously detected and filtered out because some outliers may still carry important information (Herman *et al.,* 2013; Filzmoser, 2007).

Outlier detection and filtering helps to improve the performance of predictive models. Several techniques to detect time series outliers are proposed in literature (e.g., Tsay *et al.*, 2000; Weng & Shen, 2008). However, distance-based and density-based approaches are widely used (Rahman *et al.,* 2012). A distance-based approach determines the distance between a data point and its nearest neighbour, and compares the distances for all of the data. On the other hand, density-based approaches compare the density of a data point's neighbourhood with that of its neighbour's neighbourhood. The underlying principle is that a data point that is far from its neighbours is likely to be an outlier (Knorr & Ng, 1997). As such, distance-based approaches barely detect local outliers while density-based are not good at finding global outliers, where local outliers are extreme relative to its neighbours and global outliers are outlying with respect to the majority of data points (Rahman *et al.,* 2012).

Single-step and sequential procedures are often used for outlier detection, whereby all outliers are identified at once in single-step procedures as opposed to successive elimination or addition of datum in the sequential procedure (Davies & Gather, 1993; Liu & Spencer, 2004). Typically, sequential procedures delete outliers based on control charting where outliers are identified outside three data standard deviations on a normality assumption (Woodall, 2004). Any identified outliers are removed and control chart limits are recalculated. These two steps are performed recursively until the process is statistically stable i.e., no further outliers can be detected. This procedure is known as 'classical outlier analysis' (Ben-Gal, 2005).

Chapter Summary

Chapter 2 has provided a literature review on economic performance assessment. More insight into two objectives for this study i.e., the development of EPFs and subsequently, the derivation of the EPI were provided. The factors that influence economic performance and the critical role of process control in improving economic performance were discussed. In addition, EPA methodology steps proposed by Wei & Criag (2009b) for controller performance assessment studies formed the theoretical framework for this study. A historical-data benchmark was relevant to this study. Moreover, particle size was identified as the most economically significant controlled variable for the milling circuits. Lastly, a strategy to consult experts at the industrial operation and conduct a plant survey was planned for EPF development.

The next Chapter discusses the significance of process monitoring for fault detection. Criteria used to select an appropriate process monitoring method are also presented.

CHAPTER 3: PROCESS MONITORING AND FAULT DETECTION

Chapter Overview

This chapter discusses the significance of process monitoring for fault detection. To this end, model and data-based approaches are first distinguished with more emphasis on the data-based approach. The regression analysis technique for model development, and the Shewhart control chart are discussed to address two aspects of this study i.e., a method for reliable EPF development and a strategy for developing the industrial process monitoring tool. Fault identification characteristics are discussed, and common faults in milling circuits are identified in partial fulfilment of the study objective to investigate fault detection with EPFs.

3.1 The significance of process monitoring

Process monitoring is a continuous task of recording information, identifying and detecting process performance anomalies or faults (Isermann & Balle, 1997). A fault is an 'unpermitted deviation of at least one parameter of the process or system from the acceptable condition' (Isermann & Balle, 1997). According to Venkatasubramanian *et al.* (2003b), when a detection mechanism gives a fault signal, the fault is said to be 'detected'. By monitoring process performance over time, faults can be detected when they occur (Yin *et al.,* 2002). Fault detection is achieved through a comparison of operating data to the behaviour of a model system or by applying rules to operating data. However, process performance anomalies are commonly detected using comparisons between operating data and baseline process data. Both approaches were applicable to simulation and industrial cases, respectively.

Timely fault detection is critical for consistently satisfactory economic performance. Moreover, fault detection while the process is still within a controllable operating region allows for intervention to recover the process to normal operating conditions before significant production losses are incurred. Thus, economic benefits associated with increased uptime are delivered (Fatlin *et al.*, 1993; Zhou & Guo, 2011). On the other hand, undetected faults result in safety, environmental and economic impact, depending on the fault. Thus, fault detection and identification are important to sustain satisfactory process performance as discussed in Section 3.3.

Real-time process monitoring evaluates and updates process performance with changes in process conditions (Grimshaw *et al.*, 1998). Reliable process observations improve timely fault detection rates and corrective action (Venkatasubramanian *et al.*, 2003a). On the other, log-based monitoring analyses process performance trends post-processing, in order to evaluate or monitor current performance based on these trends (Mitchell *et al.,* 2008). Long-term process evaluation for process optimization purposes is also supported by log-based process monitoring. Moreover, predictive process performance models are commonly developed with historical data (Kano & Nakagawa, 2008; Woodall *et al.*, 2004). Although the level of detail differs, both real-time and log based process monitoring are important and beneficial depending on the objectives that are to be achieved (Barton, 2013).

While process monitoring methods have been classified as a function of time i.e. real-time or log-based, they can be further classified broadly into model-based and data based approaches (Dvorak & Kuipers, 1991; Serpas, 2012). The next sections discuss these two classes.

3.2 Process monitoring approaches

According to Tatara & Cinar (2002), data-based process monitoring is a generally predominant method used to detect changes in an industrial process from historical process knowledge. For the purpose of this study, process monitoring with empirical models and statistical process monitoring are further distinguished. The first method consisted of models developed from historical data.

3.2.1 Process monitoring with empirical models

Process data is commonly used to develop empirical models of important process variables. Unlike the model-based approach, these models are more dependent on the availability of quality historical data and may even be developed without any insight on the physics of the process (Jearkpaporn *et al.,* 2005; Qin, 1998; Yin *et al.,* 2002). Empirical models developed from historical analysis require as much process data as possible, especially in cases where inferences are made with the models. The data must capture typical variation in the model parameters for good predictions to be made over a wide range of operating regions (Giddy, 1988). However, care must be taken to judiciously select model data since process data typically contains observations that reflect process upsets and assignable causes (Jearkpaporn *et al.*, 2005). Hence, process data quality must achieve the objectives being assessed (Kaka,1999; Kresta *et al.*, 1994).

Sliškovic *et al.* (2011) proposed the process-data based modelling procedure shown in Figure 3-1. Typically, the development of a reliable model often involves several iterations with these steps. However, some background knowledge formed from in-depth process understanding is useful to develop reliable empirical models (Hodouin, 2011).

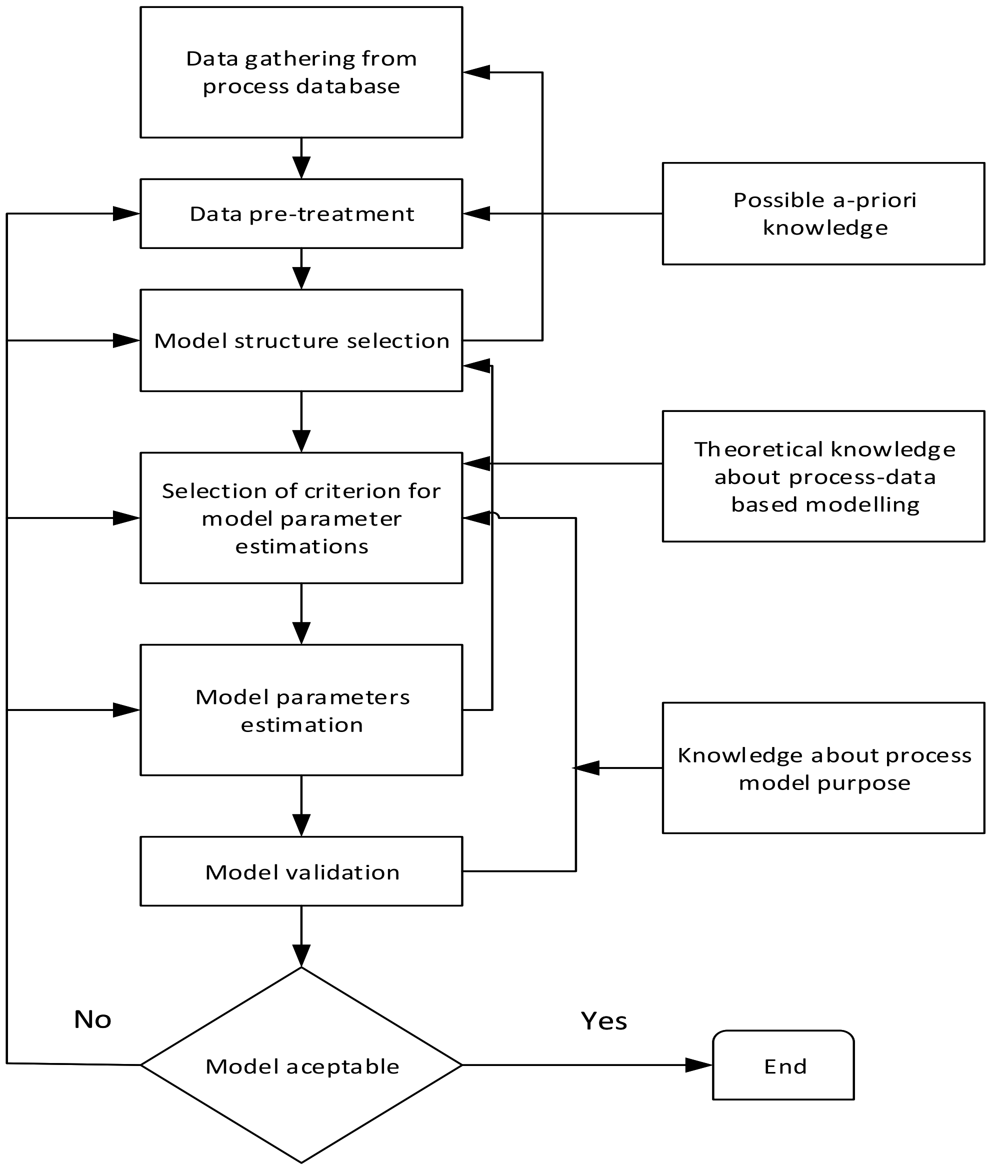


Figure 3-1: Process-data based modelling procedure (Redrawn from Sliškovic *et al.,* 2011)

The validity of empirical models is a critical criterion that ensures model representativeness. It is tested based on the significance between predicted and actual performance of an output variable of interest. When presented to new data, a valid model must possess good data fit and predict performance corresponding to the input(s). Model goodness of fit is evaluated with statistical indicators such as the adjusted R-squared.

Although predictive capability is a crucial aspect, an expert intuition is also necessary for further decision making on model appropriateness (Hamilton, 2015; Reisinger, 1997).

Most researchers (e.g., Fan & Huang, 2001; Marto & Wolfe, 1962) support the use of regression modelling to learn more about process performance. Moreover, quality is best assessed using a function, i.e., a relationship between a response variable and one or more explanatory variables (Woodall, 2016). As such, regression models have been demonstrated to account for costs associated with major grinding mill equipment (Sayadi *et al.*, 2014), for optimisation of milling circuits (Steyn & Sandrock, 2013) and for assessing the performance of milling circuits (Silva & Casali, 2015). The choice of a regression model, whether linear or non-linear largely depends on the model application. Linear regression is the most common application of regression analysis. Although it may be argued that nonlinear models are necessary, linear models are usually sufficient for monitoring (MacGregor & Kourti, 1995).

Data-based process monitoring has been demonstrated in a number of studies (e.g., Kazemzadeh *et al.,* 2009; Stover & Brill, 1998; Woodall *et al.*, 2004; Wang & Tsung, 2005), where control charts and linear regression models monitored product quality variability. The main objective for these studies was to maintain a linear profile for a data series collected at regular time intervals. Any outlying profiles pointed to an out-of-control process (Yen & Shiau, 2010). The studies applied either phases I or II, where phase I profile parameters are estimated using historical profiles. Phase II however, detects changes in the estimated parameters (Aly *et al.,* 2015). The two phases are distinguished respectively as retrospective and ongoing monitoring (Mahmoud *et al.,* 2010). Thus, phase II and is more appropriate for statistical process monitoring (as discussed in the next section).

Studies on linear profile monitoring were conducted mostly for chemical industries. Model-based process monitoring in the mineral processing industry rather focuses on nonlinear models. This is because of the challenges arising from developing linear models that are consistently representative over a wide operating range using a limited data set (Powell & Morrison, 2007; Skogestad, 2004). Moreover, data features such as the high dimensionality, input correlations and the presence of errors and disturbances make the development of accurate models for complex processes difficult (Madakyaru *et al.*, 2017).

3.2.2 Statistical process monitoring

Statistical process monitoring (SPM) is a common type of data-based process monitoring extensively applied in industry (Coetzer & Khumalo, 2006). Key process variables representative of process performance are monitored in order to maintain a state of statistical control by eliminating assignable causes of variation. The process may be susceptible to further drift outside satisfactory process performance if no action is taken (Besterfield, 2001; Woodall *et al*., 2004).

Siddiqui *et al.* (2014) classified variations into common and assignable causes. Common cause variations are inherent in a process and difficult to eliminate. However, they are controllable within some range by closed loop control. Assignable causes are unexpected random variations that influence changes in the system or process input parameters. These variations are removed in order to sustain satisfactory process performance (Besterfield, 2001; Woodall *et al*., 2004).

SPM tools identify assignable causes and detect changes in process performance. Although the basic concepts behind these traditional tools are still valid, they are not applicable to cases where the process dynamics are non-negligible or cases where the process variables are highly correlated. Moreover, SPM tools are incapable of accommodating large amounts of data. In cases with dependent process variables, multivariate statistical process monitoring (MSPM) is commonly used (e.g., Arteaga & Ferrer, 2002; Boque & Smilde, 1999; Yoo *et al*., 2002).

MSPM techniques capture correlations between process variables to minimize the probability of missing an out-of-control event due to correlation inherent in the data (Moody, 2014). These techniques have been demonstrated in several studies with many successful industrial applications for fault detection (e.g., Desborough & Miller, 2002; Yuan & Lennox, 2009). Active statistical process monitoring has been applied in other studies (e.g. Hachicha *et al.,* 2012; Ibrahim, 1996), to complement concepts from automatic process control with SPM techniques. However, this study focused on univariate statistical process monitoring.

The variability of a single process variable is monitored about a statistical measure of the variable in univariate statistical process monitoring. However, selecting a single process variable may not be sufficient to monitor a milling circuit as a large number of key process variables should be monitored to assess process performance (McClure *et al*., 2014). Hence, univariate statistical process monitoring appears to be restrictive and inappropriate for complex processes (Hachicha *et al*., 2012).

Interactions between process variables are common in milling circuits and information contained therein enhances process understanding. However, each process variable is assumed to be independent and correlation structures between process variables are disregarded. By so doing, essential multivariate qualities in process data are deconstructed and useful information is lost. Consequently, process deviations are either not detected for processes with high correlations amongst variables or false alarms may be generated. Alternatively, monitoring multiple process variables discretely provides a poor and costly design for univariate monitoring that results in the generation of an uncontrollable number of alarms (Yin *et al.*, 2002). Therefore, multi-predictor EPFs are also developed in this study to investigate the feasibility of process monitoring with all key controlled variables for the primary mill circuit.

3.2.3 The role of control charts

Control charts are a form of time series plots that are applied in univariate statistical process monitoring. The use of control charts is summarised in (

Figure **3-2**), where trial control charting tests whether consistently predictable results are produced, in an attempt to bring the process to stable and predictable operation (Benneyan, 2001; Steiner & Mackay, 2000).

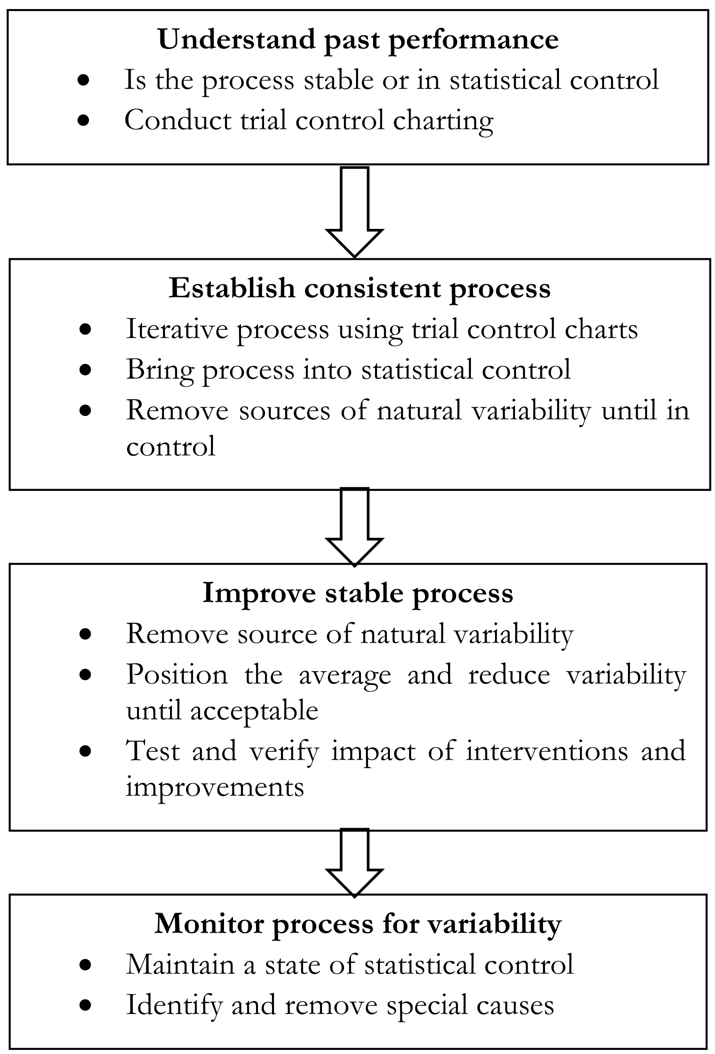


Figure 3-2: Roles for control charts (Redrawn from Benneyan, 2001)

3.2.4 Criteria for implementing control charts

The following criteria tests the appropriateness of implementing control charts (Box & Luceno, 1997):

1. Is a control chart an appropriate tool for application? The appropriateness of applying a control chart in process monitoring depends on whether or not a stable period exists. A process variable with stable variance but a drifting mean requires automatic process control strategy to reduce variability.
2. Which type of control chart should be used? Control chart selection is influenced by the objective for applying a control chart i.e., whether for real-time process monitoring, problem-solving, or assessment of process stability. In addition, the function of control charts is also considered i.e., whether for variable data or quality attributes data. Attribute control charts are more useful for attributes data (Gulbay & Kahraman, 2006).
3. Where should control limits be placed? Successful statistical process monitoring is ensured by correctly set control chart limits, which crucially define acceptance and rejection regions for satisfactory performance. Therefore, careful thought must be put when determining control chart limits.

Based on this criteria, the Shewhart control chart was applied in this study to monitor economic performance. This chart is understood by a wide range of audiences and is useful for detecting significant variability by monitoring economic performance over time (Benneyan, 2001). Subsequently, root causes can be established and corrective action taken (Alt & Smith, 1998).

3.2.5 Shewhart control chart

Shewhart charts are constructed with three distinctive features: a central line (CL) representing the target economic performance for the process, an upper control limit (UCL), and a lower control limit (LCL). The control limits are typically three standard deviations (as shown in Equation 3-1) from the economic performance derived from a representative stable normal operating period. This period reflects all the natural process variance when process performance specifications are met (Kresta *et al.*, 1994).

$$
\begin{aligned}
LCL &= CL - 3\sigma \\
UCL &= CL + 3\sigma
\end{aligned}
\qquad \text{3-1}
$$

where σ - standard deviation from target economic performance

The Shewhart chart assumes that the process subject to common cause variation will remain in a state of statistical control, where a process variable remains close to the set point. Therefore, control chart limits will reflect the variability produced by assignable causes such that out-of-control data lies outside the control limits as shown in Figure 3-3. This chart becomes an insensitive method for diagnosing assignable causes when these limits become wider than necessary (Wood *et al.*, 1998). Furthermore, the use of unfiltered process data makes this chart susceptible to noise and increases the rate of false alarms.

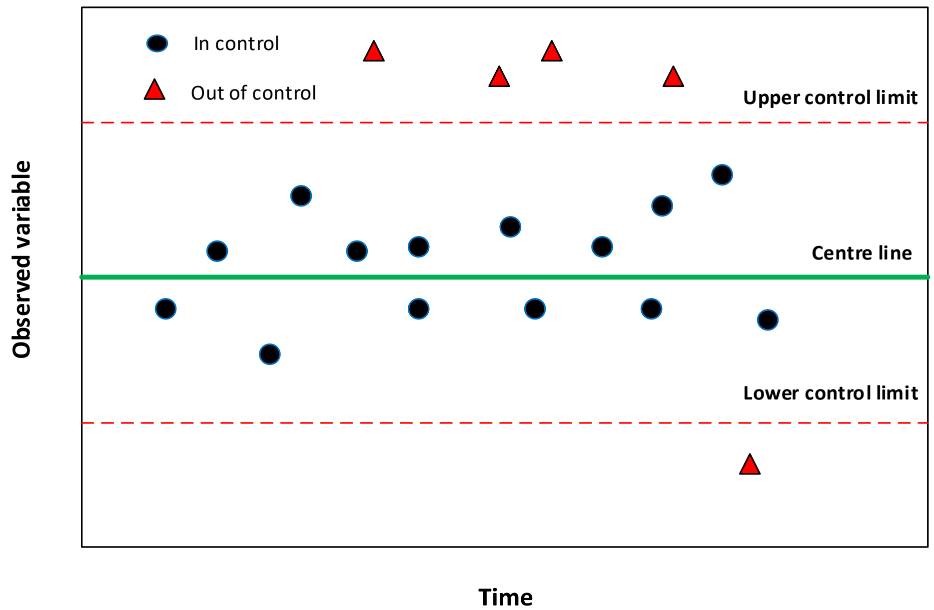


Figure 3-3: Shewhart control chart

Shewhart control chart rules for degrading performance

A Shewhart control chart provides early insight on degrading economic performance through identifying an out-of-control process from a time series plot of process performance. Table 3-1 gives the rules for identifying out of control signals (Duncan, 1986).

Table 3-1: Control chart rules

Test	**Criterion**	**Number of points**
1.	Points above Upper Control Limit (UCL) or below Lower Control Limit (LCL)	1
2.	Zone A n of n+1 points above/below 2 sigma	2
3.	Zone B n of n+1 points above/below 1 sigma	4
4.	n points in a row above or below the centre line	9
5.	Trends of n points in a row increasing or decreasing	6
6.	Zone C—n points in a row inside Zone C	15
7.	n points in a row alternating up and down	14
8.	Zone C – n points in a row outside Zone C	8

The following describes the information presented in Table 3-1.

Test 1: Extreme Points

Test 2: Two out of three points in Zone A or beyond

Test 3: Four out of five points in Zone B or beyond

Test 4: Runs above or below the centre line

Test 5: Linear Trend Identification

Test 6: Oscillatory Trend Identification

Test 7: Avoidance of Zone C

Test 8: Run in Zone C

The corresponding control chart zones are illustrated in Figure 3-4.

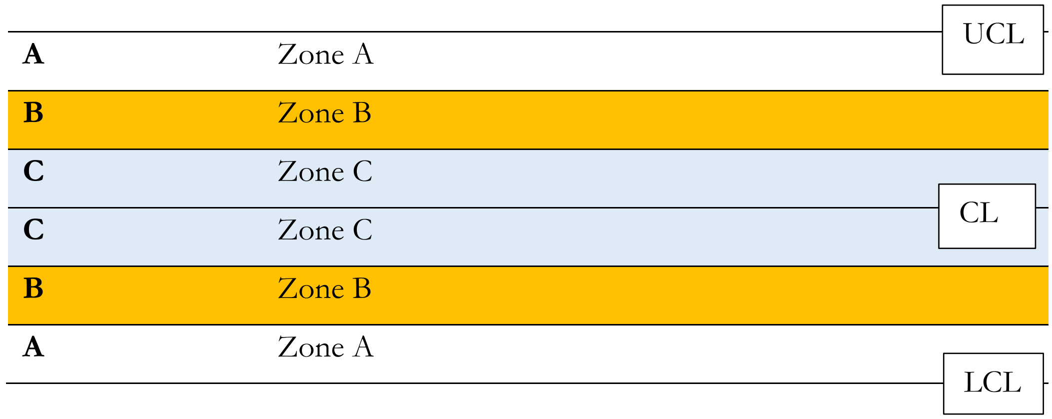


Figure 3-4: Control chart zones

In the next section, three fault identification characteristics are discussed and an overview on common faults in milling circuits is provided.

3.3 Fault characteristics and common faults in grinding mill circuits

3.3.1 Fault characteristics

Three features that distinguish faults i.e., classification, rate and frequency of occurrence are discussed in subsequent sections.

3.3.2 Fault classification

Faults are broadly classified into five categories based on where they occur. Controller malfunction, actuator failures, structural failures, human intervention, sensor failures and process disturbances are illustrated in Figure 3-5 (McClure *et al.*, 2014; Venkatasubramanian *et al.*, 2003b).

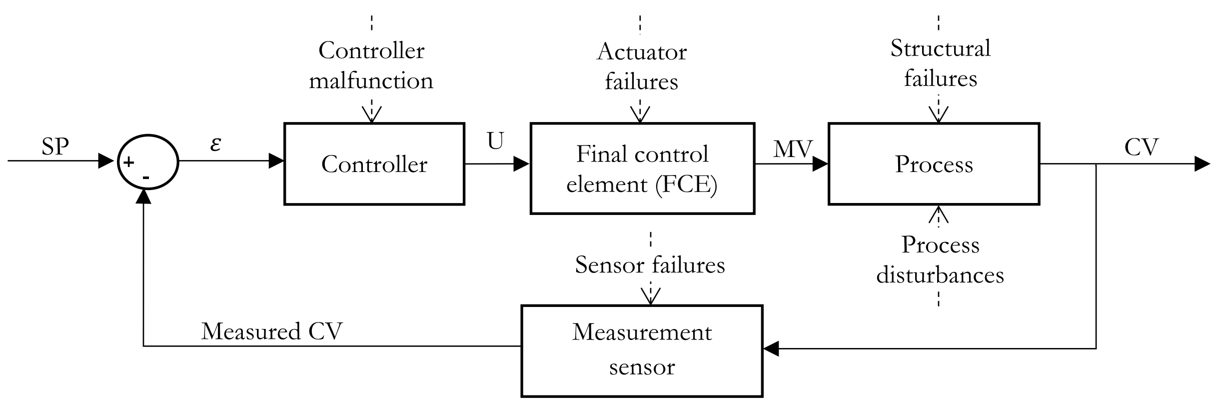


Figure 3-5: Fault classification within a process (Adapted from Venkatasubramanian *et al.*, 2003a)

The automation of industrial processes makes them vulnerable to controller, actuator, and sensor failures. Sensors provide critical feedback signals for the control of a process. Faults may occur as a malfunctioning sensor, a fixed failure, a drift or an out-of-range failure (Arzen, 1991; Barton, 2013). Sensor faults result in differences between measured and actual values of process variables. As such, prompt fault detection and timeous accomplishment of corrective actions of sensor failure are necessary to avert the deviation of plant state variables beyond acceptable limits (Gertler, 1998). Structural failures e.g. mill failure occur in process unit equipment. In some instances, inappropriate human intervention may result in a fault (Buchanan & Bessant, 1985; Riascos *et al.,* 2004). However, this is now less common especially with the growing reliance on automated processes. Process disturbances manifest when there are difficulties to sufficiently attenuate input variation. For example, variation in ore feed size distribution may result in high circulating loads to produce effects such as mill overfilling and hydrocyclone spigot choking.

3.3.3 Rate of occurrence

Faults are also characterised according to the rate of occurrence. Cha & Agrawal (2014) classified the time dependency of faults into abrupt, incipient and intermittent categories as shown in Figure 3-6 (where *f* is the fault size and *t* is the time).

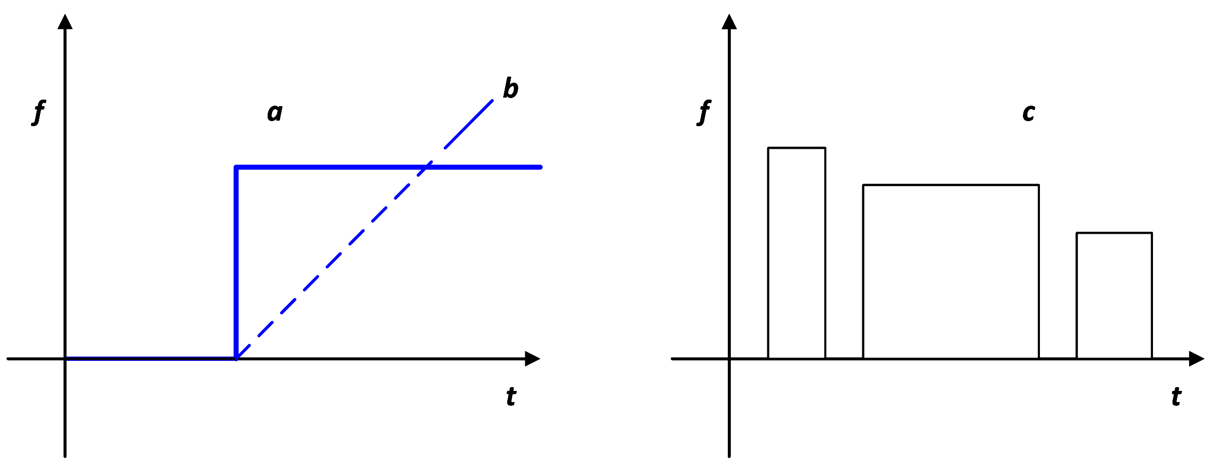


Figure 3-6: Time dependency of faults (a) abrupt (b) incipient (c) intermittent (Adapted from Cha & Agrawal, 2014)

Abrupt faults occur instantly and are referred to as 'short" faults because of the sharp change between two successive data points. However, incipient faults slowly develop with time as "long" faults with a constant value over successive data points. Unlike abrupt faults with a sudden appearance, these faults are less easy to detect. Intermittent faults occur abruptly in varying sizes and for varying time intervals. In simulation experiments, abrupt faults are modelled as a stepwise function representing a bias in the monitored signal, incipient faults are represented by drift-type changes and intermittent faults are modelled as a combination of impulses with different amplitudes as cyclic, a spike (sudden increase during a short duration) or erratic faults (Cha & Agrawal, 2014; Lees, 1973; Sharma et al., 2007; Zhang & Yan, 2011).

3.3.4 Frequency of occurrence

The frequency of fault occurrences is yet another important characteristic that provides systematic strategies to prevent fault recurrence or propagation into total failures (El-Farra & Giridhar, 2008). This information is useful for diagnosing the root cause of more frequently occurring faults (Himmelblau, 1978).

In the next section, common faults in milling circuits are discussed.

3.4 Common faults in milling circuits

Although myriads of faults can occur in milling circuits, only a few frequently occur. Respondents in a web-based survey conducted by Wei & Craig (2009b) on milling circuits listed poor load cell reliability, steam and slurry build-up on sump level sensor, and continual drift in densitometers as some of the frequently faced instrumentation challenges. Furthermore, automated steel ball loading and mill load control were some of the additional challenges highlighted in milling circuit control and optimisation (Wei & Craig, 2009b). Based on these contributions, faults that could be simulated with Le Roux's SAG mill model are introduced in the next sections.

3.4.1 Drifting mill load cell

Mill load cells are commonly used to measure the mill weight (Wei & Craig, 2009b). Most modern mills operate with load cells which synchronize the mill weight, power draw, and ore feed with density control (Mular *et al.*, 1988; Wills & Napier-Munn, 2006). Since automatic process control depends on reliable measurements, mill load cells require accurate calibration (Marlin *et al.,* 1991). However, measurements are prone to variation from humidity changes, chemical seepage (of reagents dosed into the mill) or random sensor drift. Hence, sensor measurements systematically drift away from the actual weight (Dey *et al.*, 2014). An unobserved load cell fault may cause mill overload due to erroneous measurements. Therefore, corrective action such as stopping the mill to reduce the load may be required. Consequently, production and revenue losses are incurred (Wei & Craig, 2009b).

3.4.2 Steel ball overcharge

Steel ball charge provides breaking mass to support the milling process. The volume of steel balls in the mill is an important control parameter that affects breakage rates and in-mill trajectories. Moreover, mill throughput and specific power input are affected by the amount of steel ball charge maintained in a mill. Hence, additional steel balls are added whenever in-mill charge falls below the target volume (Gupta *et al.*, 2013). SAG mills normally operate with ball charge level of between 8 to 21% (Wills & Napier-Munn, 2006; Morrell & Valery, 2001).

Accurate measurements of steel ball charge still present a challenge since mill absorbed power not only depends on ball level but also on operating parameters that include pulp density and liner configuration (Bartsch *et al.*, 2008; Rupare *et al.,* 2013). Due to this limitation, plant operators usually infer ball level from power draw and bearing pressure measurements which may result in steel ball overcharge faults (Clermont & De Haas, 2010) Occasionally, crash stops are performed to obtain more accurate ball load measurements based on the volume percentage of steel balls in the mill. A crash stop involves instantaneously cutting off all mill feed streams during steady state mill operation and completely grinding out the ore (Clermont & De Haas, 2010). These practices seek to address lack of better online measurements of in-mill ball level.

About 40-45% of the total comminution costs are attributable to grinding media and 5-10% to linear wear, hence the control of steel ball charging is highly important (Radziszewski, 2013; Rupare *et al.*, 2013). Thus, ball media overcharge is associated with direct economic impact from excessive liner wear rates, increased steel ball consumption, as well as frequent overload trips and downtime (Pokrajcic & Morrison, 2008; Rupare *et al.*, 2013). Furthermore, an additional operating cost is incurred for power consumption since specific mill power is directly proportional to the amount of steel ball added at a particular time (Williams *et al.*,1986; Almond & Valderrama, 2004; Silva & Casali, 2015).

3.4.3 Poor quality steel ball charge

Milling circuits are operated with an objective to minimize steel ball consumption (Wei & Craig, 2009a). Spero *et al.* (1991) and Aldrich (2013) relate steel ball wear rate to ball quality (i.e., composition and metallurgical properties), the ore feed (i.e., particle size and hardness), mill properties (i.e., size, speed and liner profile), milling environment (i.e., in mill conditions such as slurry density) and milling circuit parameters (e.g., circulating load and residence time).

Quality issues in steel ball media induce process disturbances (Moema *et al.*, 2009; Singh, 2003). Furthermore, poor quality steel ball charge not only affects consumption rates but milling effectiveness and power consumption (Morrison & Powell, 2006). Therefore, manufacturers conduct quality checks of standard physical and mechanical specifications before supply. Steel ball chemical composition and hardness profiling tests are two of the crucial quality control procedures followed to ensure on-specification steel balls.

Steel abrasiveness is an important hardness factor that determines the absolute wear rate of steel balls (Aldrich, 2013). Despite quality checks, casting defects such as shrinkage and gas porosity are common in some batches supplied to industry (Jankovic, 2003; Moema *et al.,* 2009). Casting defects in steel balls result in minimized steel ball wear resistance, leading to premature steel ball breakage. Consequently, rapid steel ball wear rates are experienced and steel ball consumption is increased.

3.4.4 Ore hardness variation

Highly variable ore feed characteristics are manifested by intrinsically variable orebody composition (Hunt *et al.*, 2013). Ore feed hardness affects the control of grinding mills because of its effect on actual grinding mechanics (Egbe & Abubakre, 2013). Comminution behaviour, energy requirements, the product particle size achieved and hence mineral liberation, are directly influenced by ore hardness (Mwanga *et al.,* 2015).

When ore hardness significantly increases by 90% for example (as cited in Coetzee *et al.*, 2008), fault conditions manifest. The mill build-ups from increased grinding time and recirculating coarse sized particles to become throughput limiting. Consequently, production rate is lowered in order to stay within the rated mill power draw constraint (Wills & Napier-Munn, 2006.; Powell *et al.*, 2009). Typically, additional steel balls are charged into the mill to counteract the effect of the fault. However, this takes significant time for equilibrium to be reached and hence, it is more effective for long term circuit improvement (Forssberg & Schonert, 2012).

Chapter Summary

Chapter 3 has provided a literature review on process monitoring methods. Model and data-based methods were distinguished and a discussion on the significance of statistical process monitoring highlighted the importance of timely fault detection. Regression modelling was identified as a suitable method for EPF model development, and the Shewhart control chart for process monitoring. Five fault classes were distinguished, and a characterisation of the rate and frequency of fault occurrence was presented. Finally, four common faults in milling circuits were identified and their consequences, highlighted. Therefore, this

Chapter addressed three aspects i.e., the use of regression modelling for EPF model development with industrial data, strategies for developing the industrial process monitoring tool and for assessing the feasibility of fault detection with EPFs.

The next Chapter discusses a critical site survey at the industrial Concentrator plant. Insight is provided on process operations, economics, and control as a critical step to EPF development with industrial data

Chapter 4: Industrial Primary mill circuit Survey

Chapter Overview

This chapter reports on information acquired from the industrial operation during preliminary and critical site survey visits. A review of primary mill circuit operation, control, and economics provides a basis for reliable EPF development, as discussed in Chapter 2. Key objectives driving operating strategies are discussed and an overview of the control philosophy is presented. Furthermore, the factors influencing economic performance are identified. Finally, historical data is used to assess the primary mill circuit's economic performance in monetary terms.

4.1 Introduction

A week long preliminary site visit was conducted at the industrial concentrator plant with an objective to appreciate the Concentrator plant operations. The key outcome of the preliminary site visit was to identify a suitable scope for the industrial case study. Issues that related to process operation, control and economics (Appendix A) were studied. After identifying a suitable scope, a critical site survey was conducted to acquire an in-depth understanding of the primary mill circuit's operation as presented in this Chapter.

4.1.1 Concentrator plant overview

Operations at the industrial Concentrator plant consist of Dry and Wet sections. Crushing and coarse grinding stages constitute the Dry section, while milling, flotation, and downstream thickening operations make up the Wet section.

Minerals are liberated from the ore through a multi-staged comminution circuit to ensure sufficient liberation since the ore is one of the hardest to beneficiate (Rule & DeWaal, 2011). Sufficient liberation of mineral values is important for downstream flotation, which intermittently occurs after milling stages in a Mill-Float-Mill-Float (MF2) circuit configuration. The scope of this study was limited to the primary mill circuit as highlighted in the MF2 circuit flow diagram shown in Figure **4-1**.

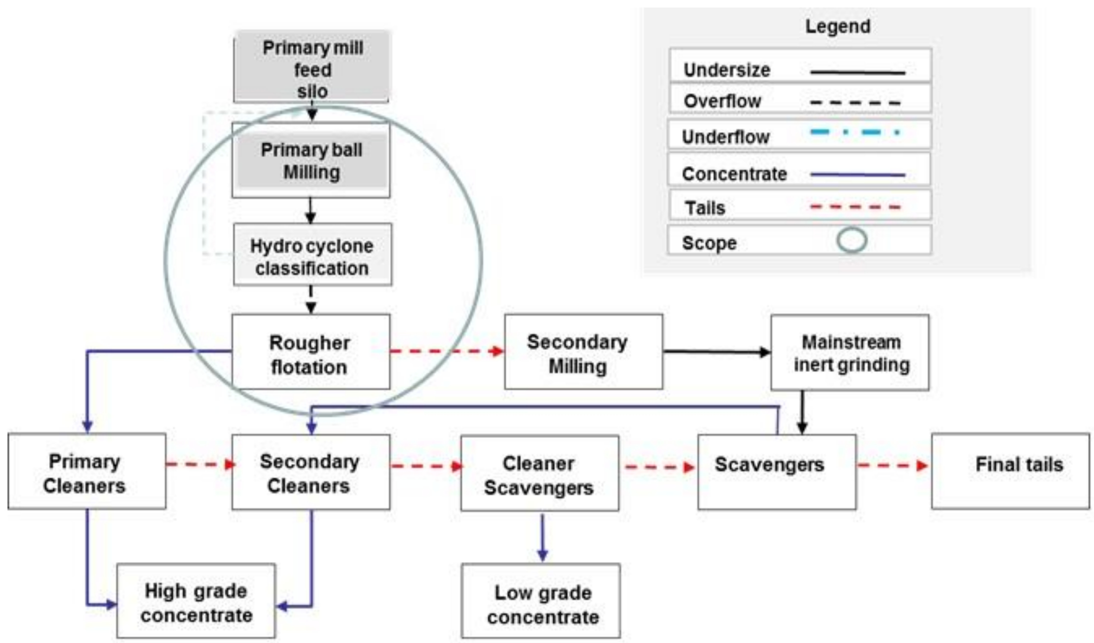


Figure 4-1: Concentrator plant flow diagram

4.1.2 Primary mill circuit process description

The primary mill circuit comprises the primary ball mill, sump, hydrocyclone cluster and rougher flotation units. A process narrative of the circuit is presented below:

Ore with a nominal size of 100% passing 8mm is reclaimed from the primary mill feed silo and fed into a 17.5 MW grate discharge ball mill of diameter 7.92m and an effective grinding length of 11.28m. Water is added at the mill feed end to improve in-mill rheology. Steel balls with a top size of 70mm are charged into the mill as grinding media. During the milling process, ore pulp and some steel ball scats are discharged through a 15x28mm slotted aperture discharge screen. Oversize scats are conveyed to the mill scats bunker, while undersize material gravitates to the primary mill discharge sump.

Collector and promoter reagents are dosed into the primary mill discharge sump for pulp conditioning in preparation for downstream processing. Make-up water is added to the primary mill discharge sump for density control and diluted pulp is pumped to a duty hydrocyclone cluster. The primary ball mill is operated in a closed circuit with a hydrocyclone cluster which separates coarse and fine particles into underflow and overflow streams respectively. The underflow stream of coarse particles gravitates back to the ball mill for additional grinding, while the overflow stream of fine particles is delivered to the flotation circuit for mineral recovery. The overflow stream is gravity fed to a rougher flotation splitter box, where it is split into two parallel rougher flotation banks. Reagents (frother, collector, promotor, depressant and activator) prepared to a specified strength are dosed into rougher feed boxes with additional controlled dosing down the bank.

Rougher flotation feed typically has a target grind of between 40-55% passing 75µm. It is treated in two flotation banks, each consisting of seven 100m^3 flotation cells. The first three flotation cells in bank #1 are Dorr-Oliver forced-air type and the last four are self-aspirating Wemco flotation cells, while bank #2 only operates Dorr-Oliver forced-air type flotation cells. The different bank design facilitates plant-scale optimisation test work. Despite the mechanical difference between the banks, metallurgical performance i.e. upgrade ratio and recovery of the two banks is reported to be comparable. Each bank produces a first and second grade concentrate stream that is delivered to respective primary cleaner flotation cells. The number of flotation cells reporting to either the first or second concentrator grade sump is variable. Rougher tailings from each rougher flotation bank report to the rougher flotation tailings sump before downstream processing.

The process control hierarchy given in Chapter 2 is discussed for the primary mill circuit in the next section.

4.2 Process control hierarchy

The primary mill circuit is controlled with an objective to meet operating and economic objectives as discussed in following process control hierarchy:

4.2.1 Instrumentation

Table 4-1 lists key instrumentation for the primary mill circuit, and a brief description for some instruments is given.

Table 4-1: Primary mill circuit instrumentation

Milling	
Measured variable	**Instrument**
Primary mill feed silo level	Ultrasonic level transmitter (%)
Primary mill feed rate	Electromechanical weightometer (t)
Primary mill discharge particle size	Ultrasonic particle size analyser (µm)
Mill load	Load cell (t) Inferred from bearing pressure
Mill inlet water	Magnetic flowmeter (m^3/h)
Sump level	Ultrasonic level transmitter (%)
Sump make-up water flow rate	Flowmeter (m^3/h)
Hydrocyclone slurry flow rate	Magnetic flowmeter(m^3/h)
Hydrocyclone feed pressure	Pressure transmitter (kPa)
Hydrocyclone feed density	In-line densitometer (t/m^3)
Flotation	
Rougher feed Pd grade	On-stream XRDF stream analyser
Froth velocity	Froth cameras (mm/s)
Reagent dosage rate	Magnetic flowmeters (m^3/h)
Rougher cell pulp level	Ultrasonic level transmitter (m)
Rougher cell air flow rate	Air flowmeter (m^3/h)

The instrumentation listed in Table 4-1 is commonly used in milling circuit operations (Wei & Craig, 2009b). Many process variables are monitored online in order to achieve efficient process performance in response to changes in system inputs. The ultrasonic particle size analyser obtains a running average of the particle size distribution as an ultrasonic wave propagates through the primary mill discharge stream. Ultrasonic spectroscopy is typically applied for particle sizes of between about 10nm and 1000 µm (Riebel & Löffler, 1989). This measurement method is preferred relative to alternative offline techniques because it minimizes handling errors and the time taken to generate measurements.

Elemental on-stream X-ray diffraction and fluorescence (XRDF) analysers measure rougher feed stream samples. An average of the specific gravity and palladium (Pd) content is continuously generated from 5-minute measurements. Measurement reliability depends on the extraction of a representative sample, and it is checked for consistency with offline analysis. On-stream XRDF measurements are more suitable for rougher flotation assay-based control, rather than for metallurgical accounting purposes. The analysis of multiple streams to provide simultaneous comparisons between feed, concentrate and tails for measured streams is one major advantage of XRDF analysers.

Froth cameras are installed on each rougher flotation cell to capture and analyze froth surface images. Several froth features including froth velocity, froth stability, and bubble size distribution measurements are extracted from the froth images. Furthermore, measures of concentrate contribution from each individual cell are determined based on the froth velocity.

4.2.2 Base control

Table 4-2 presents the controlled variables regulated with base control. The control of solids (ore and steel ball) feed rate, circulating load, mill feed water, hydrocyclone feed flow and rougher flotation feed improves primary mill circuit stability. Effective sump control is critical to stable operation without which, an off-specification particle size product and poor flotation performance result.

Table 4-2: Base control for the primary mill circuit

Controlled variable	Control objective	Control used	Controller type
Mill ore feed	To maximise throughput	Load control	PID
Mill inlet water	To achieve target in-mill density	Ratio control	PI
Steel ball grinding media	To maintain load to steel ball ratio	Ratio control	PI
Sump level	To maintain stable operation	Level range control	PID
Sump discharge rate/Hydrocyclone feed flow rate	To achieve consistent rougher feed flow To stabilise the mass pull achieved	Cascade control	PID
Hydrocyclone feed pressure	To achieve target particle size	Ratio control	PI
Reagent flow rates into designated reagent dosage points	To condition the pulp for mineral recovery	Ratio control	PID
Mass pull	To achieve stable concentrate mass flow	Cascade control	PID

Figure 4-2 is a process and instrumentation schematic showing manipulated variables for the primary mill and floatation circuit. Only one rougher flotation cell is illustratively shown.

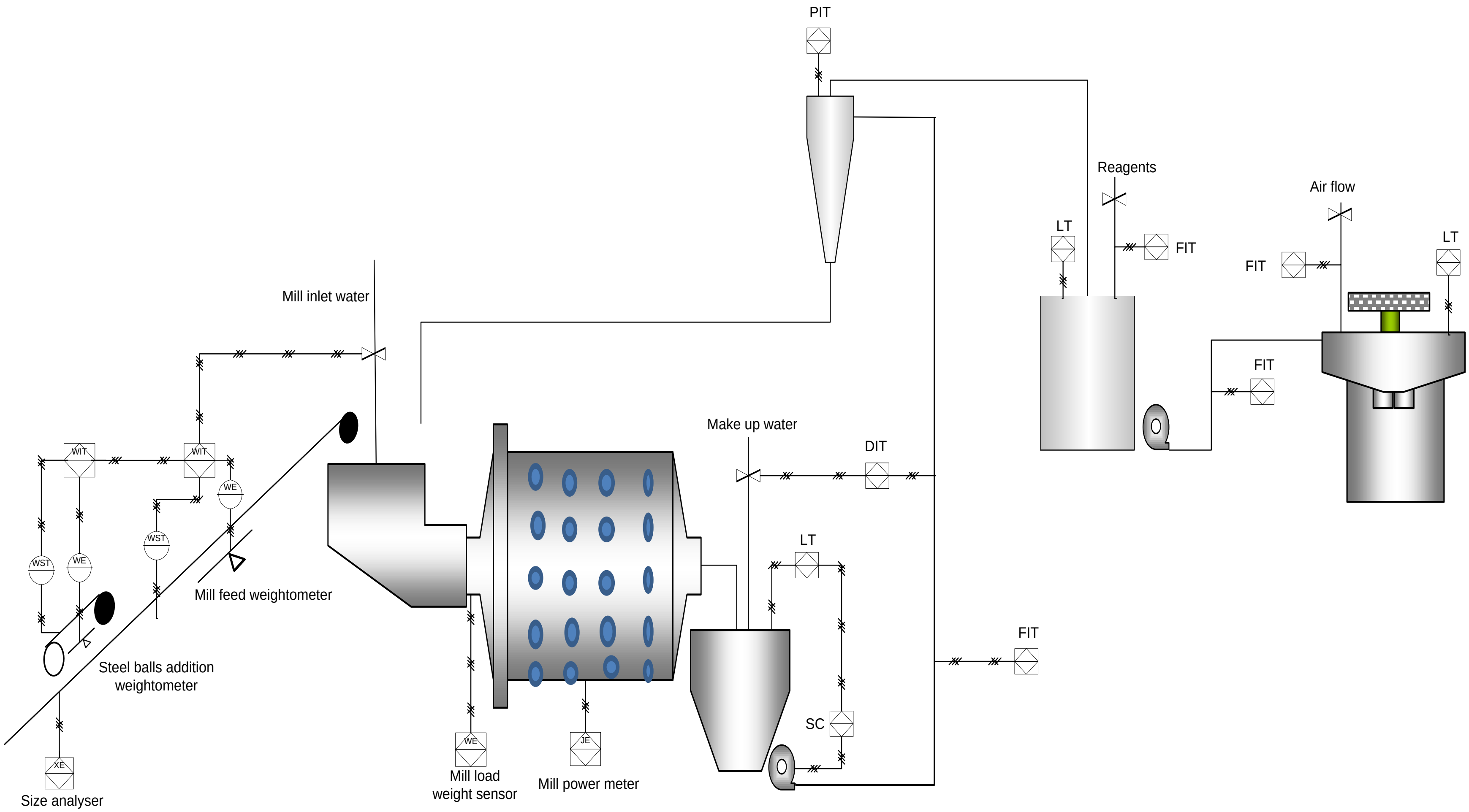


Figure 4-2: Process and instrumentation diagram

4.2.3 Advanced control

Model predictive and fuzzy logic controllers provide a consistency of control actions to optimize primary mill circuit operation, based on the following objectives:

1 Liner wear reduction;

2 In-mill density control; and

3 Target mass pull attainment

Section 0 to Section 0 discusses each of the four control objectives

Liner wear reduction

The primary mill is lined with renewable wear-resistant liners to withstand the impact of in-mill charge trajectories and grinding mechanics. Liner profiles are selected to promote the desired charge trajectories at minimum wear rate, and prolong service life since liner replacement is a substantial maintenance cost. Despite their cost, mill liners with longer service life are preferred such that labour costs associated with mill relining, and production losses incurred during reline stoppages are minimized. The primary mill load is regulate within set limits through efficient ore feed and steel ball control in order to promote desirable grinding mechanics and yet reduce liner wear rates. Mill relining typically takes place every 4-6 months dependent on the liner thickness profiles tracked during scheduled downtimes.

In-mill density control

Ore feed and water addition rates are two independent variables in the primary mill circuit operation that influence milling efficiency. Ratio control regulates ore feed rate and mill inlet water flowrate to achieve target in-mill density. Consequently, optimal milling conditions are established and mill ancillaries are safeguarded from wet or sticky conditions that arise due to poor density control. A reduction in comminution energy is an added benefit.

Increased mill inlet water yields wet in-mill conditions that result in metal-to-metal interactions between steel ball and mill liner or among steel balls. These interactions cause rapid mill liner and steel ball wear rates to consequently, increase comminution costs and flush out of the mill insufficiently ground particles. Sticky in-mill conditions arise from high in-mill density that promotes steel ball coating. As a result, grinding impact and attrition forces decrease such that mill throughput becomes limited (Wills & Napier-Munn, 2006).

Target mass pull attainment

Mass pull influences mineral value recovery into the rougher concentrate, as well as the trade-off relationship existing between mineral recovery and concentrate grade. Fuzzy logic control aims to operate the flotation circuit to a desired recipe in order to stabilize both individual cell and overall flotation bank mass pull. Thus, mass pull and target aeration rates are adjusted for each defined functional unit to stabilise concentrate flow and achieve the target overall bank mass pull.

4.2.4 Optimization level

Advanced process controllers possess functionality for online process optimisation where the following economic objectives are to be satisfied:

1 Throughput maximisation;
2 Power utilization minimization; and
3 Target peak air recovery (PAR) attainment

Throughput maximisation

Maximum economic benefits from the low-grade Plat reef ore are achieved with throughput maximisation. The optimization criterion for model predictive control (MPC) is to maximise throughput within design capacity and operating limitations, while achieving target product particle size.

Power utilisation minimisation

Milling operations are energy-intensive, and in most cases energy inefficient. In conventional ball mill technologies, only 1% of the energy is used for size reduction (Wills & Napier-Munn, 2006). To improve power utilisation (Equation 4-1), the primary mill is operated with a gearless variable speed drive. Furthermore, primary mill variable speed drives optimise mill speed based on mill load operating parameters.

$$J = \frac{P}{F \times PS} \tag{4-1}$$

Where J – power utilisation, kWh/t <75µm

F – throughput rate, tph

PS – particle size <75µm

Target peak air recovery attainment

Flotation cell airflow leaves either as bubbles in the overflowing froth or by bursting on the surface. The fraction of air overflowing as froth is known as the air recovery, which subsequently affects the separation performance between the gangue and mineral values. Peak air recovery (PAR) is an intermediate between very low and very high aeration rates, where froth velocity is high enough for a substantial proportion of the bubbles to overflow before bursting, thus recovering mineral values (Smith *et al.*, 2010).
Figure **4-3** shows the PAR at mid froth depth, between shallow and deeper froths.

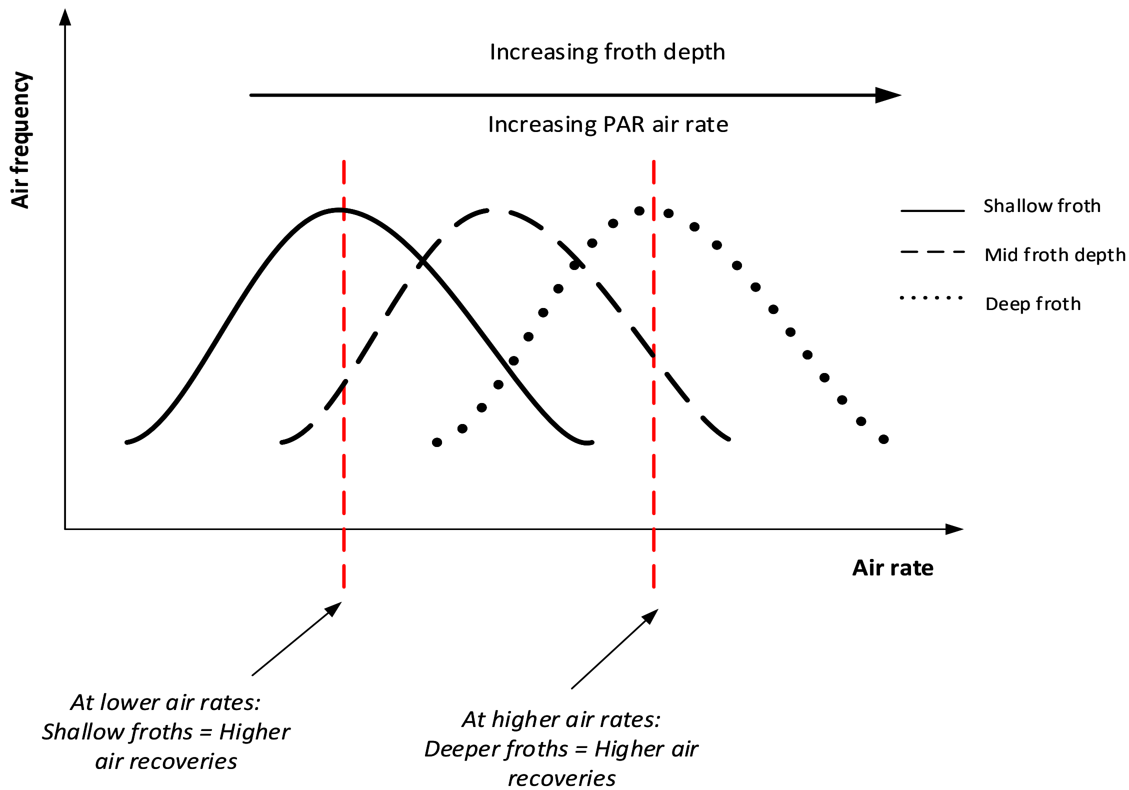


Figure 4-3: Relationship between froth depth, air rate and air recovery (Redrawn from Smith *et al.*, 2010)

Consistently operating at the target PAR continuously optimises concentrate grade and recovery. Hence, fuzzy logic control regulates aeration rate around the PAR to satisfy rougher flotation mass pull target. Empirical studies are conducted periodically to establish the optimal target PAR for each rougher flotation cell and subsequently, control limits for aeration rates.

The next section identifies and discusses key controlled variables and corresponding manipulated variables for the primary mill circuit.

4.3 Variables for the primary mill and rougher flotation circuit

The primary ball mill circuit is essentially a multi-input–multi-output (MIMO) system. The model predictive controller (MPC) used for the primary mill circuit is generally known to handle highly interacting multivariable due to its coordinated approach, and has feed forward capability. The controller's objective is to operate controlled variables close to the constraint without violating it, such that future control moves are planned by the controller to achieve this objective at any sampling instant. An optimization problem to maximize the throughput and minimise power utilisation is thus calculated as the constraints for the primary ball mill are satisfied.

Controlled and manipulated variables for the primary mill and rougher flotation circuit are listed in Table 4-3.

Table 4-3: Controlled and manipulated variables for the primary mill circuit

Controlled variable	Manipulated variable(s)
Mill power draw	Solids feed rate (ore and steel ball media)
Mill load	Mill speed
Hydrocyclone feed pressure	Number of open hydrocyclones
Mill grind size	Solids feed rate, mill & total water addition
Sump slurry level and density	Discharge rate to hydrocyclones Make-up water flow rate
Mass pull	Aeration rate, reagent dosage, and froth depth

Mill power draw is a key performance metric for the primary ball mill operation. A power metre reading and bearing pressure are used to control the feed rate into the mill to maximise power draw. Typically, an increase in both mill power and bearing pressure points to a mill load that is smaller than an optimum value. Ore feed rate is increased in such cases. However, a decrease in mill power and an increase in bearing pressure signifies an overloaded mill. When this occurs, ore feed rate is decreased to effect a corresponding decrease in both the mill power and bearing pressure.

Mill load behaviour impacts on the primary mill circuit's efficiency. Hence, mill load volume is controlled such that the mill operates at maximum available power through maximising ore feed rate as well as minimising mill speed and mill inlet water, while coarse ore ratio is maintained.

The primary mill's performance in terms of throughput, power draw and grind can be expressed as a function of mill filling in grind curves, These are used to achieve optimal mill operation through determining throughput, power draw, and grind peaks, relative to mill filling levels. The manipulated variables shown in Table 4-3, as well as the feed size distribution and ore hardness also influence the grind curve. Typically, the shape of the curves is dramatically affected by mill speed, as the mill throughput increases with mill speed, and the grind becomes considerably coarser as mill speed increases because this promotes better impact breakage. Hence, the mill speed, target mill filling is varied, based on the grind curves in order to satisfy the throughput maximisation objective.

Hydrocyclone feed pressure affects the cut-point which determines whether particles report to the overflow or underflow. A high feed pressure causes the cut point to drop and give a finer overflow. However, coarse particles transfer to the overflow stream at even higher pressures. Hence, the feed pressure is controlled to stabilize rougher feed particle size and density, by manipulating the number of open/closed hydrocyclones through a valve arrangement.

The efficiency of hydrocyclone classification and rougher flotation is significantly impacted on, by the variation in the fineness of grind. A coarse mill product results in a low liberation index, such that non-liberated particles are not recovered during flotation. The circuit also becomes throughput limiting due to a high circulating load to the mill. On the other hand, a very fine grind results in mineral losses during flotation and high energy consumption rates. Typically, the amount of sub 75microns mill product particle size (grind) lies between 40-55% for the industrial operation.

The primary mill circuit's sump level is controlled by either increasing or decreasing sump discharge pump speed to a hydrocyclone cluster. A dual PID cascade simultaneously controls sump density and level such that a stable level and density is maintained. The level PID controller drives the hydrocyclone feed flow rate set point so that the sump level is maintained at set point, while makeup water to the sump controls the density.

The schematic diagram of how MPC is applied in the primary mill can be summarised as shown in Figure 4-4.

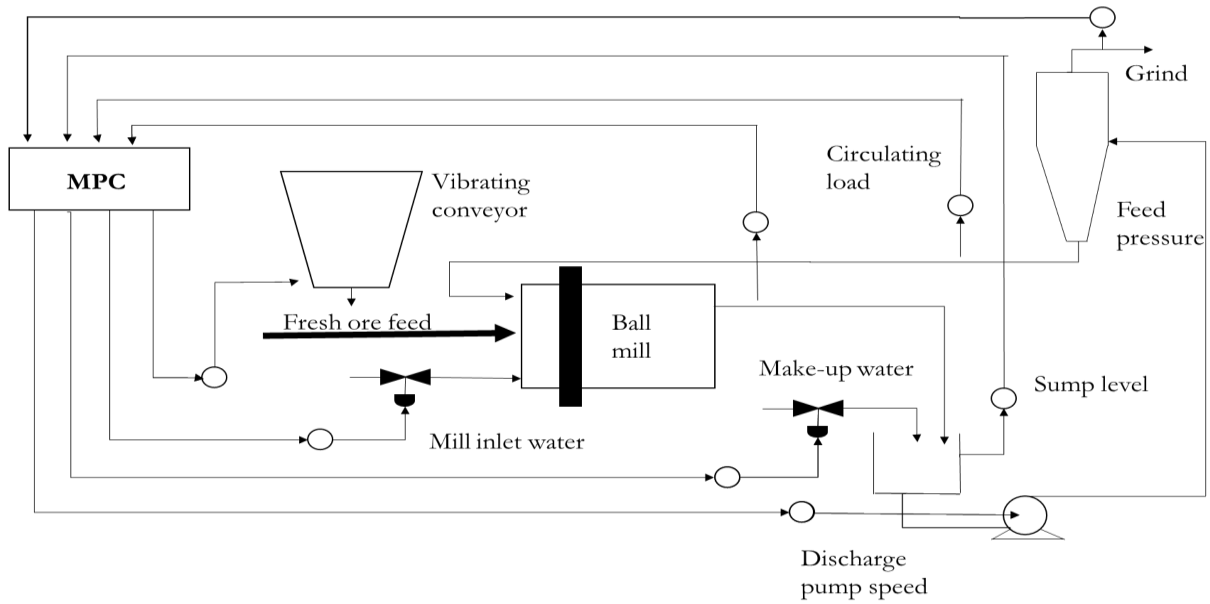


Figure 4-4 : Primary mill control

During rougher flotation, mineral recovery into the concentrate stream is achieved through mass pull control in order to optimise grade and mineral recovery at stable concentrate flow. Mass pull and air targets set per functional unit are achieved with fuzzy control. The rougher flotation circuit is thus operated to a desired recipe to stabilize both individual cell and consequently, functional unit mass pulls.

A mass pull controller calculates a mass pull flowrate from the concentrate flowrate and density. The mass pull is monitored by froth cameras, which are installed above each rougher flotation cell to perform froth image analysis. These cameras measure the amount of bubbles present, bubble size, colour as well as their direction and rate of movement. The mass pull controller manipulates flotation cell level (and hence froth depth), aeration rate and reagent dosing rate. Controlling the flotation cell level minimizes long-term variation in flotation performance due to steady-state changes in flotation feed, while airflow control assists with rapid response to disturbances. Hence, cell level is varied over a wide range for concentrate grade control, but within a defined acceptable operating window such that changes in operating conditions between cells, changes in milling performance and ore type are managed. However, the level is manipulated slowly in order to maintain setpoint tracking and achieve a stable circuit. Typically, a residence time of 30minutes is achieved in rougher flotation.

4.4 Operational performance at the Concentrator plant

Operational performance at the Concentrator plant is assessed across the three metrics shown in Figure 4-5.

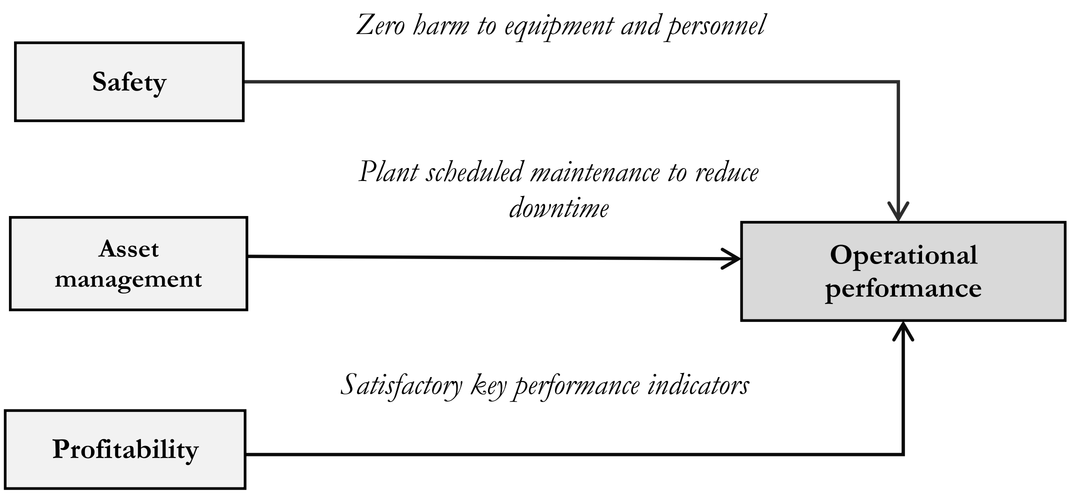


Figure 4-5: Operational performance metrics

Safety management is a priority for all the work conducted within the concentrator plant. All work is executed in strict adherence to organizational safety procedures. Preventative maintenance is an essential control implemented for employee, equipment and environmental protection amongst other key purposes. Assets are managed through scheduled preventative and predictive equipment maintenance, to enhance equipment reliability and increase the time between failures. As a result, the costs associated with inefficient processes and production losses during equipment breakdowns are minimized.

Scheduled maintenance for major primary mill circuit equipment occurs once in every two months. Mill ancillaries and peripherals that include conveyance systems (pumps, conveyor belts, as well as delivery and transfer pipes) are attended to more often. During maintenance periods, flotation cells and respective peripheral ancillaries are drained, cleaned and worn out flotation cell components are replaced. Similarly, reagent tanks and lines are also flushed out and cleaned to prevent reagent delivery pipe blockages which result in poor dosage and consequently, poor flotation performance. Instrument replacement and recalibration in the primary mill circuit is another key scope during maintenance shutdowns.

Key performance indicators (KPIs) are tracked to assess profitability and identify any gaps between actual performance and management objectives.

4.5 Process performance monitoring strategies

4.5.1 Offline sample analysis

Online assay analysis for the primary mill circuit is complemented by offline laboratory analysis. Composite samples of mill feed and rougher flotation streams (Table 4-4) are taken every shift (eight hours) for laboratory analysis. The 4E represents platinum (Pt), palladium (Pd), rhodium (Rh) and gold (Au), while 3E consists of the first three elements. 3Es are assayed for the rougher tails, as base metals and gold appear in comparatively smaller quantities.

Table 4-4: Offline sample analysis

Sample	Quality sampled
Mill feed	Particle Size (%< specified sieve sizes, mm) 4E Head grade (g/t)
Hydrocyclone streams (overflow and underflow)	Particle size distribution
Rougher feed	Grind (% < 75µm) 4E (g/t)
Rougher tails	3E (g/t)

4.5.2 Plant surveys

Annual plant surveys of milling and flotation streams are conducted to provide a critical assessment of the primary mill circuit's performance. Particle size distribution and densities for the primary mill discharge, hydrocyclone feed, rougher flotation feed and tail streams are measured during these surveys. In addition, mineral compositions the rougher feed and tail streams are determined from laboratory tests. Subsequently, the data is used to identify opportunities for debottlenecking and process optimisation.

4.5.3 Tracking key performance indicators

Budget plans for operating expenditures and production targets are forecasted each year. Performance goals are then developed from budget plans into more manageable and easily monitored performance metrics, which are implementable at operational level. Subsequently, production and financial performances are evaluated with key performance indicators (KPIs). Performance reports that track and assess KPIs are routinely generated to measure the effectiveness in achieving key business objectives, as well as to account for any variances. These reports also assess historical and current performance, forming a basis for making production forecasts through comparisons between actual performance and budget plans for each period (week, month and year). The KPIs used to evaluate concentrator plant performance are adopted for the primary mill circuit as shown in Table 4-5.

Table 4-5: Key performance indicators for the primary mill circuit

Processing	Process control	Financial
Tonnes milled	Circuit stability	Cash operating cost/3E oz produced
Final concentrate grade	Reduced variability	Cash operating cost/ Pt oz produced
3E recovery	Attainment of target operating conditions	Cash operating cost/ton milled
Plant availability		

As shown in Table 4-5, processing KPIs contribute to the revenue, which is maximized by achieving high throughputs at the target grind for an optimal 3E mineral recovery-concentrate grade trade-off. Plant availability refers to a productive period, and is assigned as a measure of plant reliability.

Process control KPIs are a measure of circuit stability and indicate whether target operating conditions are achieved. Efficient process control reduces process variability to maximise profitability. The financial KPIs consist of cash-operating cost, which is one key value lever used to maximize profitability since value drivers such as price are beyond control. Hence, process efficiency is assessed based on cash operating cost metrics i.e. a low cash operating cost per unit product infers a more efficient operating period relative to a high cash operating cost per unit product. The balance between the cash operating cost and the primary milling circuit's metallurgical performance is very critical for the low-grade ore processed in the circuit.

4.6 Factors influencing economic performance

The external economic environment influences the profitability primary mill circuit operations. Global supply and demand trends significantly influence metal prices. Hence, one of the top ten business risks in mining operations is metal price volatility (EY, 2013). Electricity, reagent and steel ball grinding media unit pricing, as well as 3E metal prices are subject to cost inflation and exchange rate movements. Inflation and exchange rate trends, as well as metal price movements are presented in Appendix B.

Increased scale of production together with improved electricity and consumable utilisation are two strategies employed to maximise profit. Efforts towards reducing the consumption of electricity and consumables, consistent with achieving satisfactory performance is continuously made. Since maximizing profit is not entirely dependent on minimizing operating costs, efforts are also made to achieve target production tonnages.

Based on the discussions and derivations in this section, the following conditions improve the economic performance of the primary milling circuit:

1. Throughput maximisation and 3E mineral recovery control
2. Efficient consumable and electricity consumption
3. Effective scheduled maintenance
4. Improved market conditions (exchange rate, metal pricing)
5. Supply conditions (consumable prices, electricity tariffs)

The first three factors are manageable within operations, while the remaining two factors are beyond the control of the organization.

4.6.1 Economic performance assessment of primary mill circuit

The primary mill circuit's economic performance was derived so that suitable benchmark data sets for the process monitoring tool could be identified. Financial KPIs referred to in Section 4.5.3 were derived, as well as the profit realised for the years 2012-2016. In order to mask confidential industrial data, normalised values (determined as shown in Appendix C - Equation 1) were presented. Detailed cost elements for the primary mill circuit are shown in Figure 4-6. Appendix D shows normalized consumption rates for the cost elements.

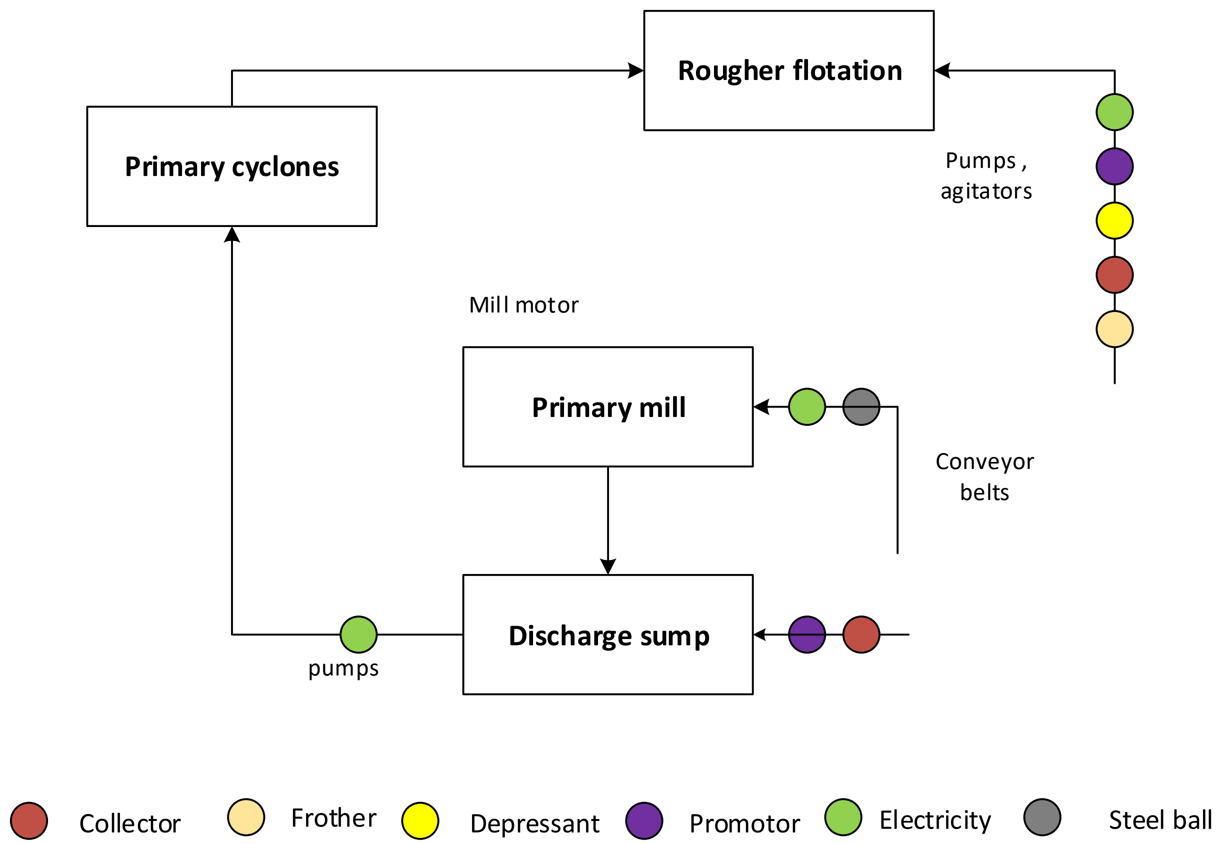


Figure 4-6: Operating cost elements

The cost distribution of major elements in the primary mill circuit for the years 2012 to 2016 are presented as percentages in Figure 4-7.

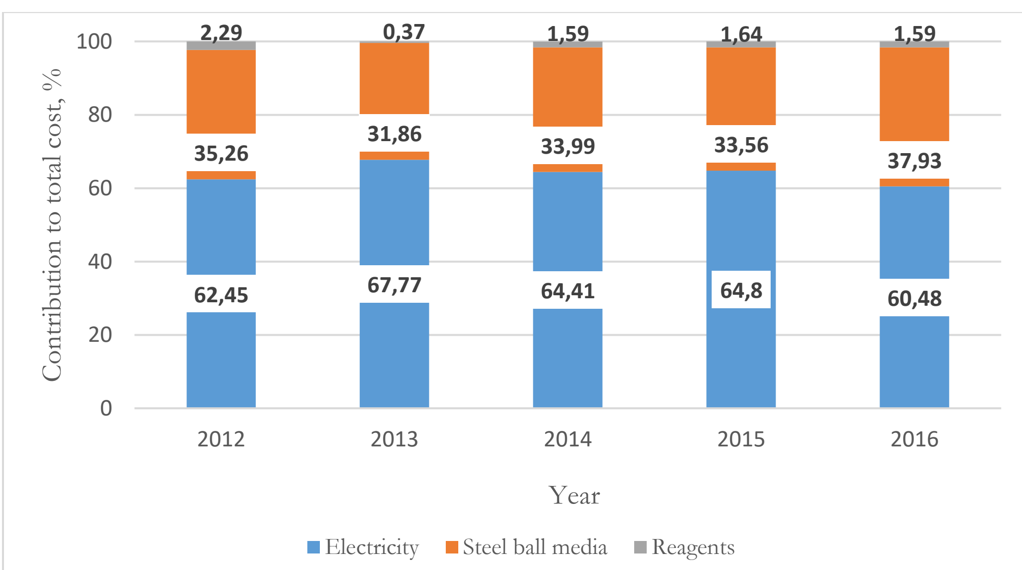


Figure 4-7 : Distribution of operating costs

In agreement with several literature (e.g. Matthew & Craig, 2013; King, 2001), a similar trend is observed throughout the years, where electricity costs (derived from equipment listed in Appendix E) contribute the largest percentage towards the assessed cost structure. Steel ball costs are a significant cost that is influenced by the amount of tonnage processed (Appendix F). Reagent cost contributed the least to overall cost structure. The significant drop after the year 2012 was based on a management decision to lower reagent dosage rates (depressant, collector and promotor) as a cost-cutting initiative (Appendix D). This decision was supported by laboratory test work results, which showed satisfactory performance at the lower dosage rates.

The financial KPIs identified in Table 4-5 were also derived for the primary mill circuit for the years 2012 to 2016 (Appendix G). To this end, cash operating costs only constituted variable costs that included consumables (steel ball grinding media and reagents), and electricity. Maintenance materials and supplies, other utilities i.e. water and compressed air, as well as labour for both scheduled and unscheduled maintenance were not included in the assessment based on the same reasoning used for the cost associated with mill liner replacement. Constant fixed costs and consumable unit prices were assumed in the performance assessment. Although industrial electricity tariffs vary according to seasonality, time of use, peak demand and the power factor, a flat rate was assumed for electricity unit cost.

Appendix I presents the metal sales revenue, operating cost and profit realised from operating the primary mill circuit. Rougher flotation feed was assumed the final sellable product. However, an adjustment factor was applied to account for downstream beneficiation. The spot metal prices and calculation formulae used in this assessment are presented in Appendix J and Appendix C, respectively.

Chapter Summary

Chapter 4 has reported on critical site survey findings at the industrial Concentrator plant. A background to the primary mill circuit operation, process control and economics was provided. The strategies implemented for economic performance monitoring were presented, and factors affecting economic performance were identified as well as illustrated. It was possible to derive historical economic performance for the primary mill circuit in monetary terms. This was a necessary step towards developing a benchmark for the process monitoring tool. The next Chapter presents a research methodology for developing a reliable EPF and subsequently, a process monitoring tool for the industrial primary mill circuit. Furthermore, the economic impact of three different simulated fault events is assessed to investigate fault detection with EPFs.

CHAPTER 5: RESEARCH METHODOLOGY

Chapter Overview

This Chapter first provides a background on the research design and introduces industrial and simulation case studies. A research methodology is presented to address objectives for the industrial case study i.e., to develop a reliable EPF with industrial data, and to derive an overall economic performance index for the primary mill circuit. Similarly, methodology steps to assess the feasibility of fault detection with EPFs is presented for the simulation case study.

5.1 A background on case study research methods

The application of case study research is relevant in many fields and disciplines. Case studies give an insight into the context of the study and illustrate the main point (Fry *et al,* 1999). Wei & Craig (2009c) regard case study as an appropriate research method used to examine and evaluate the relevance of existing theoretical propositions and practice. In addition, past studies and complex issues are explored to gain an in-depth understanding (Gulsecen & Kubat, 2006).

There are generally three types of case studies i.e., exploratory, descriptive, and explanatory (Ponelis, 2015). Exploratory case studies critically focus on any significant observation that serves as a point of interest to the researcher. For instance, a hypothesis can be derived or cause-and-effect relationships tested (Yoon & Hwang, 1995). Descriptive case studies on the other hand, rather describe a significant observation and finally, explanatory case studies examine the significant observation to the extent of explaining it (Zaidah, 2007). Jankowski *et al.* (2011) classified retrospective, snapshot and longitudinal case study research according to the time dimension. In retrospective case studies, a past significant observation is studied. However, snapshot case studies are more concerned with examining the significant observation within a particular period. Lastly, longitudinal case studies compare a significant observation over time.

According to Baxter & Jack (2008), single or multiple case studies can be conducted. Multiple case studies enable an understanding of the differences and similarities between cases (Stake, 1995). Furthermore, they allow for a wider exploration of the observation and hence, are considered to be more reliable since a significant observation can be analysed both within and across situations (Baxter & Jack, 2008; Yin *et al.*, 2002).

Case studies are conducted as qualitative and quantitative research. Qualitative research is common in exploratory case studies where data are collected through direct encounters. Often, verbal data is acquired using interviews, discussions, and surveys as research tools rather than measurements. The information gathered is indicative and can only be analysed in an interpretative manner (Williams & Dame, 2015). Quantitative research on the other hand, involves generating numerical data or information that is converted into measurements that may be statistically analysed. Typically, experiments and surveys are used in quantitative research (Creswell, 2003).

Quantitative research often involves finding evidence to either test predictive hypothesis or investigate generalizability, reliability or causality. Generalizability investigates the extent to which the results of a study can be applied beyond the sample to a larger population. A previous study is repeated to establish the consistency of its findings when reliability is investigated. However, causality is concerned with cause and effect relationships (Heale & Twycross, 2015). For example, static and dynamic relations among system variables and parameters are investigated so that a system's behaviour is described in quantitative mathematical terms (Isermann & Balle, 1997). To this end, statistical models are applied to establish and assess relationships as well as test the relationship strength and significance, typically with correlation and regression analysis (Bax, 2004; Chi, 1997).

Unlike quantitative research, qualitative research is not limited to rigidly defined variables. Complex questions that are difficult to resolve or understand by quantitative research are examined further. The findings of qualitative research are instructive and based on the sample., hence, not usually generalizable. Consequently, it is difficult to replicate or make systematic comparisons with the qualitative approach (Bryman & Bell, 2007; Hoepfl, 1997). The key disadvantage of a qualitative approach is the subjectivity associated with a researcher's perception. Hence, the interpretation of research findings is usually researcher biased.

On the other hand, the research problem is stated in very specific terms when a quantitative approach is used (Frankfort-Nachmias & Nachmias, 1992). The researcher remains objectively separated from the study or investigation and only needs to appreciate the assumptions inherent within different statistical models (Wei, 2010). Thus, quantitative research possesses a high reliability level and is easily replicable when the methods used are well explained (Creswell, 2003). However, the outcomes of quantitative research are limited to those outlined in the research objectives, and this is unlike qualitative research. To maximise the benefits of both qualitative and quantitative approaches, triangulation is used to synthesize both approaches and improve research validity and reliability (Denzin, 1998).

The next section introduces the industrial case study and presents the research methodology.

5.2 Industrial case study

The following objectives were defined for the industrial case study:

1. To develop a reliable EPF with industrial primary mill and rougher flotation data;
2. To derive the circuit's benchmark economic performance;
3. To assess the feasibility of industrially implementing an online process monitoring tool for the circuit, using one key controlled variable; and
4. To assess the feasibility of incorporating additional key controlled variables in the process monitoring tool.

5.2.1 Case study data sources and research instruments

This study used a triangulation of literature survey of academic books, journals and electronic sources, semi-structured interviews, a survey of the industrial operation, and simulation experiments to gather primary and secondary data. The literature survey provided a good basis to construct interview questions and contextualize literature findings to the objectives of this study.

5.2.2 A background to EPF development

The development of EPFs was informed by expert knowledge and literature findings. Based on the EPF developed by Edwards & Vien (1999) at laboratory scale, operating data was empirically analysed using a linear second-order model with first term interactions (Equation 5-1). Furthermore, model predictive control in its common form uses a linear model to represent the dynamic process within separate time periods, and a quadratic objective function is used to drive controlled variables back to their set points (Beigler, 2010). Thus, the selected model is justified.

$$\mathrm{P} = \beta_o + \sum_{i=1}^{k} \beta_i CV_i + \sum_{i=1}^{k} \beta_{i,i} CV_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} \beta_{i,j} CV_i CV_j + \varepsilon \qquad \textbf{5-1}$$

Where β_o and β_i are regression coefficients

P – profit function

CV – economically significant controlled variables

i,j – ith observation of jth controlled variable

ε – residual

Single-predictor (SP) and multi-predictor (MP) linear regression EPFs were developed between CV and mineral recovery data. Single-predictor EPFs were developed with the most economically significant CV, and subsequently used to develop an algorithm for the process monitoring tool. On the other hand, multi-predictor EPFs were developed using all economically significant CVs for the primary mill circuit to further assess the feasibility of incorporating more CVs into the process monitoring tool and account for underlying CV interactions. Key revenue and cost metrics associated with the primary mill circuit were incorporated to improve the representativeness of the EPF.

5.2.3 A background to the process monitoring tool

Primary mill circuit monitoring was investigated with a Shewhart control chart to detect degrading economic performance. To this end, a reliable single-predictor EPF was first developed with industrial data from a satisfactory operating period. Subsequently, a base case EPI that represented the historical benchmark was derived as the Shewhart control chart mean. It was anticipated that degrading economic performance could be detected from process observations using control chart rules discussed in Section 0.

5.2.4 Selection of economic performance scenarios

The main aim for long term process monitoring is not only to track performance, but diagnose the reasons for good and bad performance. As such, three economic performance scenarios i.e., base, best, and worst cases were identified to firstly, validate the historical benchmark and secondly, to investigate the proposed process monitoring tool working concept. Benchmark validation was necessary to provide a credible process monitoring tool, and for appropriate process action to be taken.

The selection of performance scenarios was influenced by factors summarised in Figure 5-1.

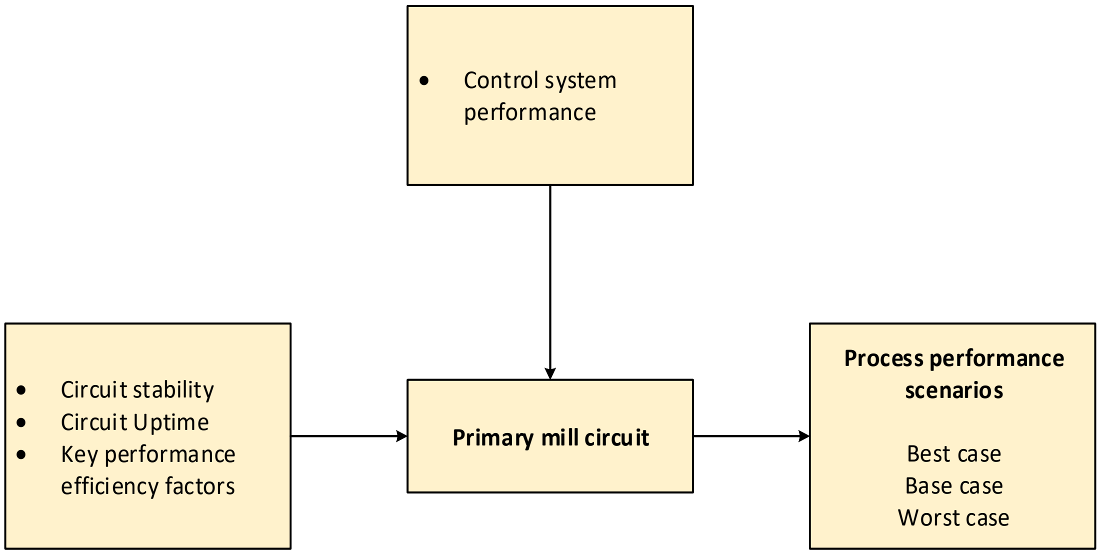


Figure 5-1: Factors influencing primary mill circuit performance

The base case scenario consisted of satisfactory performance from normal operating conditions. The best case represented a good operating period with minimal performance variation. Finally, the worst case scenario was derived from a period with unstable circuit operation and large performance variation.

5.2.5 Methodology for EPF development

The theoretical framework of Wei & Craig (2009b) presented in Section 2.7 was used to develop research methodology steps for this study as discussed in the following sections:

5.2.6 Determining information requirements for EPF development

A thorough examination of the primary mill circuit flowsheet was conducted for an appreciation of the type of historical production data captured. Historical data for the period January 2012 to April 2016 were available for assessment. Consultations and semi-structured interviews with site experts provided further information on the process (Appendix A). In addition, data logged into control room log-sheets, laboratory assaying reports, production and financial reports were analysed. Appendix K lists data of interest, which included key controlled variables, revenue and cost elements relevant to the primary mill circuit for EPF development.

5.2.7 Identifying key controlled variables

An in-depth process understanding from literature survey and site expert opinion informed the selection of key controlled variables for the circuit. Two Plant Metallurgists, a Process Control Metallurgist, and Project Engineer were each asked to select key controlled variables in terms of economic significance, based on the impact of controlled variables on the operating objective, i.e. to maximise throughput and at that throughput, optimise mineral recovery. Table 5-1 ranks controlled variables for the primary mill and flotation circuit based on the industrial experts' input.

Table 5-1: Controlled variable ranking in terms of economic significance

Controlled variable	**Percentage agreement amongst consulted experts**
Mill load	100
Particle size	100
Mass pull	75
Sump slurry density	50
Hydro-cyclone feed pressure	25
Sump level	25
Mill power	0

At least half of the experts selected mill product particle size, mill load, sump slurry density and mass pull as the most economically significant CVs, and this was in agreement with most literature sources (e,g,. Hodouin, 2011; Le Roux *et al.*,2013; Pomerleau *et al.*, 2000; Ramasamy *et al.*, 2005). None of the consultants selected mill power as it does not influence the operating objective and hence, revenue elements. Therefore, these four CVs were adopted as predictors for regression analysis in EPF development.

5.2.8 Retrieving the required information

The data of interest identified in Appendix K were retrieved from the plant historian, as well as archived production, laboratory and financial reports. Online data for both standby and duty equipment (where relevant) were retrieved from the Plant Historian in thirty-minute time stamps. The time stamp was nominal for retrieving large amounts of data since a shorter time stamp significantly slowed down data retrieval. Offline assay data was available from laboratory archives in eight-hour time stamps. Both online and offline data were available in Microsoft Excel format.

The following control measures were exercised for efficient and correct data retrieval from the Plant Historian:

1. Listing all the data to be accessed from the plant historian.
2. Accurately identifying plant historian data tags corresponding to data of interest.

3. Ensuring the inclusion of both standby and duty equipment, as necessary.

5.2.9 Pre-treating the data

Integrating and cleaning data

Online data were rolled up into shift averages in Microsoft Excel to correspond with the sampling frequency for laboratory assay-data. Thereafter, the data were organized into meaningful data sets to minimize errors associated with handling the large amounts of data. Related data were classified into separate folders as cost, revenue and CV data. The cost folder consisted of electricity, reagent and steel ball consumption rates. Correspondingly, the revenue folder consisted of the mineral recovery, rougher flotation feed assays, rougher tail assays and mill throughput data. Lastly, the CV folder consisted of data identified in Section 5.2.7.

Illogical and anomalous data entries that were negative, or labelled 'Not connected', 'NaN' and 'ERROR' were detected in online process data. These data elements likely resulted from faulty instrumentation or measurements taken during plant downtime periods. Furthermore, some data elements were missing in laboratory assays and online measurements. These faulty data were handled in MATLAB as follows:

Outlier data

Outliers were identified as controlled variables and mineral recovery data elements lying outside three sigma lower and upper control limits (LCL and UCL). The outliers as well as values corresponding to identified outliers were deleted so that functional relationships between variables and their data were preserved. This step was performed to twice in order to minimize outlier influence on regression modelling. Moreover, doing this ensured that a reasonably representative amount of data was available for EPF development. In contrast, data quality would be compromised due to loss of useful process data variation from an iterative deletion process with classical outlier analysis.

Missing data

Efforts were initially made to recover any missing data although none of the data was recovered. The use of complete data vectors was important in subsequent methodology steps. Hence, missing data and corresponding elements for other variables were deleted. Data imputation was not considered to avoid the risk of introducing bias.

5.2.10 Investigating data reduction

The amount of data available for EPF development and economic performance assessment after pre-treatment must be representative of the period assessed. Data equivalent to one year was considered to be representative and sufficient for the period being assessed (Appendix C– Calculation 2). Since too many deletions would result in less representative EPFs due to significant loss of information, variables (CV or mineral recovery) with too many deletions were excluded from the regression analysis.

5.2.11 Investigating data normality and correlations

The normality assumption was tested by plotting quartile-quartile (Q-Q) normality probability plots for CV and mineral recovery data in order to assess the appropriateness of applying statistical tests. A scatterplot matrix was plotted and corresponding bivariate correlation coefficients were determined for all CVs and mineral recovery to determine data correlations. A correlation coefficient of at least 0.7 suggested a strong relationship between the investigated CVs, between which a joint economic performance function would be derived (as discussed in Section 2.7).

5.2.12 Simplifying assumptions

Simplifying assumptions were made for the process operation, process control, and process economics as follows:

Assumptions for process operations

1 There were no significant configuration changes in the primary mill circuit during the reviewed period.

2 Historical changes in reagent types and steel ball sizes had a negligible influence on operating conditions.

3 There were no analytical and transcription errors in laboratory assay results.

4 The particle size-mineral recovery EPF was quadratic

Assumptions for process control

1. The MPC was performing well and hence process data fit a normal distribution.
2. There were no measurement lags in the data. Typically, plant data is appropriately time shifted to account for time delays, and lagged to account for any autocorrelations in the data (Remes *et al.,* 2006; Smith *et al.,* 2004).
3. All control loops were well maintained throughout the reviewed period.

Assumptions for process economics

1 In order to assess the sensitivity of process conditions (i.e. factors within the control of industrial personnel) on economic performance, the economic environment was assumed constant. Hence, cost element unit prices, the exchange rate, and 3E basket price were fixed.
2 Electricity unit cost was equivalent to the industrial flat rate.
3 Plant overheads and maintenance costs were constant and hence not included in the assessment.
4 Economic performance for the primary mill circuit was equivalent to the profit before fixed costs.
5 The rougher flotation concentrate was the final sellable product. However, an adjustment was made to the metal basket price to account for downstream beneficiation.

5.2.13 Identifying benchmark data set

As previously highlighted, the benchmark data set was identified to achieve two purposes i.e., to train the EPF model, and to derive the primary mill circuit EPI. Since EPFs change with time, the timeliness of this data set was considered important. Hence, the benchmark data set consisting of 21 shifts was identified from a recent processing period, through the following steps:

Five performance metrics that represented key economic objectives for the primary mill circuit (i.e. electricity consumed per ton milled, production cost per ton milled, tonnage processed, 3E mineral recovery and profit) were assessed to identify a representative benchmark. The profit realised from primary mill circuit operation summarised these factors and was therefore, used as the criterion to assess economic performance.

5.2.14 Validating the selected benchmark

Three economic performance scenarios i.e., best, base and worst case performances were used to validate the selected benchmark. Data equivalent to seven shifts was used for each economic performance scenario. The EPI for each shift was derived and plotted onto a Shewhart control chart. It was expected that base case EPIs would lie around the benchmark while the best case and worst case EPIs would lie above and below, respectively.

5.2.15 Identifying approaches to EPF development

EPFs were developed using two comparative approaches referred as process variable analysis (PVA) and financial elements analysis (FEA) in this study. The financial profit and mineral recovery were used as respective profit functions. Subsequently, an economic performance function between the primary mill circuit CVs and mineral recovery was modelled using both SP and MP second-order regression analysis for the PVA approach. In the FEA approach, financial profit derived from the metal sales revenue and unit level costs was used. Formulae for the following calculations are presented in Appendix C.

Process variable analysis

EPF single-predictor and multi-predictor linear regression models were developed as a function of CV and mineral recovery data as shown in Equations 5-2 and Equation 5-3, respectively.

$$\text{EPF}_{PVA}: MR = f_{PVA}(CV_{PS}) \tag{5-2}$$

$$\text{EPF}_{PVA}: MR = f_{PVA}(CV_{all}) \tag{5-3}$$

Where CV_{PS} – particle size controlled variable

MR - mineral recovery (%)

CV_{all} – all controlled variables

Financial elements analysis

Financial profit was derived as shown in Equation 5-4 to Equation 5-6:

$$\text{P} = \text{R} - \text{C} \tag{5-4}$$

Where P - financial profit (ZAR)

R – 3E metal sales revenue (ZAR)

C – operating cost (ZAR)

$$\text{R} = \text{f}(\text{F}, \text{BP}_{adj}, \text{HG}, \text{MR}) \tag{5-5}$$

Where F - throughput rate (tph)

BP_{adj} - adjusted basket price (ZAR/oz).

HG - 3E head grade (g/t)

MR - mineral recovery (%)

The basket price was derived from a prill split percentage (adopted from May 2016), since platinum is mined as part of a basket of metals with each metal priced differently. Spot metal prices and exchange rates as at 06

June 2016 were adopted (Appendix J), and an adjustment factor of 0.65 was used to account for downstream beneficiation. The cost was derived as below:

$$\mathrm{C} = \mathrm{f}(\mathrm{c_i}, \mathrm{u_i}) \qquad \textbf{5-6}$$

Where c_i – cost element consumption rate (units)

u_i - cost element unit price adapted from Concentrator data for April 2016 (ZAR/unit)

Subsequently, the EPF was developed using multi-predictor linear regression, as shown in Equations 5-7.

$$\mathrm{EPF}_{FEA}: P = f_{FEA}(CV_{all}) \qquad \textbf{5-7}$$

Where $\mathrm{EPF}_{\mathrm{FEA}}$ - EPF derived from financial elements analysis

$\mathrm{CV}_{\mathrm{all}}$ - particle size, mill load, sump density, and mass pull

5.2.16 Identifying EPF development strategies

The following two strategies were investigated:

1 EPF development with base case data

2 Searches for EPFs throughout pre-treated historical data

In the first case, both PVA and FEA were investigated for SP and MP linear regression EPF models. Sliding window searches were applied in the PVA approach due to computational limits and a prior knowledge on the limited likelihood for valid EPFs with this approach. Valid EPFs possessed good model fit (with an $\mathrm{R}^2_{\mathrm{adj}}$ threshold value of at least 0.6) and reliable predictive capability.

5.2.17 EPF development with base case data

A sample size of 100 shifts was further selected for EPF model training, and 50 shifts for testing EPF validity during the identified base case period. These sample sizes moderated the effects of very large and very small sample sizes. Furthermore, they were representative of the amount of data available for analysis.

5.2.18 Searches for valid EPF

Based on the assertion of Hodouin (2011), steady-state changes in process disturbances induce a perpetually transient economic performance curve (Figure 5-2). Several studies have supported these findings (e.g., Bauer *et al.*, 2007; Cutler & Perry, 1983; Contreras-Dordelly, 2000; Craig & Henning, 2000; Gupta *et al.*, 2013; Herbst & Lo, 1996; Muske & Finegan, 2001; Oosthuizen *et al.*, 2004). As such, it was reasonable in this study to assume that different EPFs are generated each time a different steady state is attained. From this perspective, it was likely that poor EPF accuracy would result over a large operating window. Therefore, a reasonably sized sliding window that sufficiently captured steady states was applied to search for valid EPFs. To this end, a window sampling scheme and window size were determined.

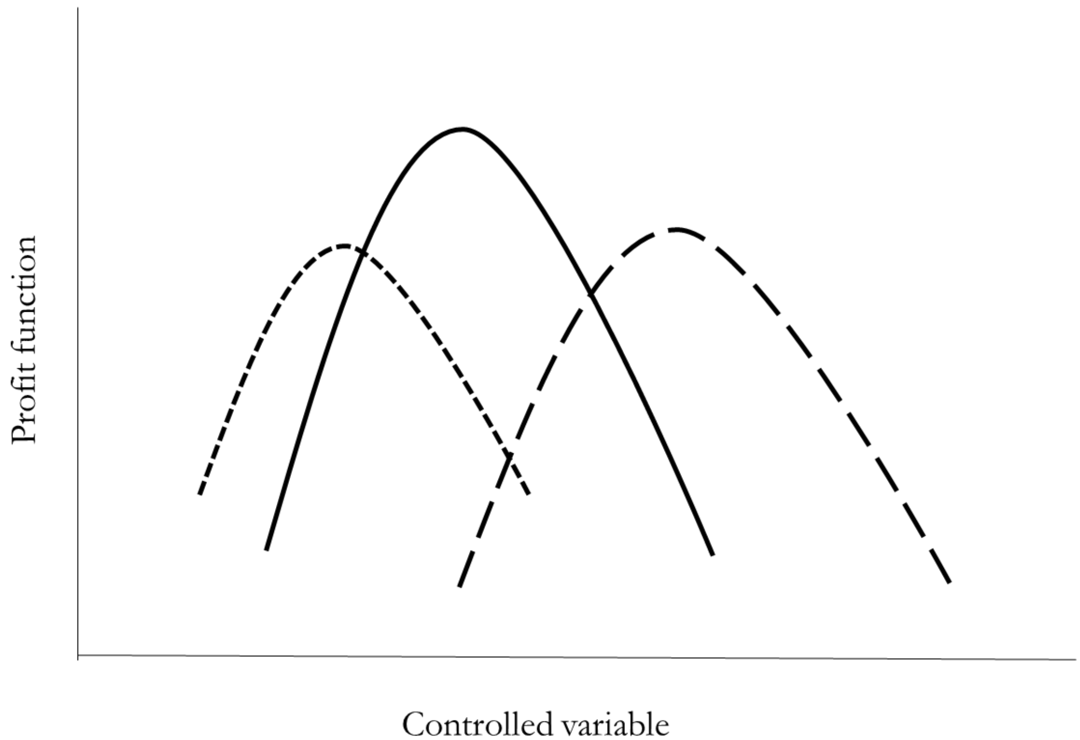


Figure 5-2 : Transient performance curve

Determining window sampling scheme

Sequence-based and timestamp-based sliding windows are two common window schema (Braverman *et al.,* 2009). Previous data elements cease to be significant and only the most recent ones (as relevantly defined) are considered for analysis in a sequence-based window. Hence, the sequence-based window is more appropriate for cases where data elements have regular, fixed sampling intervals for all variables. A timestamp-based window on the other hand, analyses all data elements that lie within a specified time interval. Data elements for the timestamp-based window may vary over time as opposed to a fixed number of data elements when the window size is specified (Babcock *et al.,* 2002; Wang & Tsung, 2005). In this study, a sequence-based window of fixed size is applied. The earliest shift (based on time) expired from the window sample at each window slide

Determining window sample size

Window sample size can affect statistical tests by either making them insensitive (at small sample size) or overly sensitive at very large sample sizes. Small window sample sizes generally result in too little statistical power to identify significant results, and data are easily over-fit to produce artificially good results. However, effects such as variable correlations are initially found to be statistically significant until at a very large sample size where almost any effect is significant (Hair *et al.*, 2010).

For this study, window sample size were large enough to cover the period during which steady state was assumed. Thus, a window size equivalent to two weeks (i.e., 42 shifts) was regarded to be sufficient. Moreover, it constituted a representative fraction of the data amount available for analyses. For further comparison, a window size of one week (i.e., 21 shifts) was investigated.

5.2.19 Performing sliding window iterations

Sliding window iterations were performed, and the following measures were plotted for each window slide iteration:

1. Window sample mean, standard deviation and the relative standard deviation (RSD) for all CVs and mineral recovery
2. R^2_{adj} for model developed with window sample data, and for model developed between mineral recovery and CV data for a consecutive window ($R^2_{adj,pred}$)
3. Mineral recovery predictions for a consecutive window

Window mean, standard deviation and RSD were used to observe and compare variability across windows. Regression coefficients for EPFs with above threshold R^2_{adj} values were evaluated based on a calculated p-value of less than 0.05. Subsequently, a reduced regression equation consisting of significant predictors was developed and tested for reliability. A reliable EPF exhibited valid mineral recovery predictions for test data in a consecutive window.

5.2.20 Investigating measurement lags

EPF models between the mineral recovery in a preceding window and CV data in a subsequent window were developed to investigate the possibility of measurement lags. Hence, test results ($R^2_{adj,test}$) were determined for each window slide.

5.2.21 Developing a process monitoring tool

The process monitoring tool was developed with a valid and reliable single-predictor EPF. Predictions for the primary mill circuit's economic performance would be made with this EPF. It was necessary to first review all the computations performed, prior to implementing the process monitoring tool in the industrial operation.

5.2.22 Determining the overall economic performance index

The PVA approach was used to estimate the EPI for the primary mill circuit since the FEA approach had been demonstrated in Section 4.5.3. Time fluctuations for the variables were discretized into a histogram and the EPI was derived with Equation 5-8

$$EPI_{PVA,overall} = \sum_{j=1}^{M} F_j (EPF_{Valid})_j \tag{5-8}$$

where

EPI_{PVA} - average economic performance index for the PVA approach

F_j – economic performance for each bin interval

EPF_{valid} - valid single-predictor or multi-predictors' EPF

j –the bin number

M – total number of bins

The optimal bin width was determined using Equation **5-9** (Scott, 1979).

$$\mathrm{B}_w = 3.49\mathrm{s} \times M^{1/3} \tag{5-9}$$

where

B_w - bin width

s - estimated standard deviation,

M - number of bins.

Generally, 5-20 histogram bins were sufficient (He & Meeden, 1994; Knuth, 2013).

5.2.23 Testing the process monitoring tool for implementation feasibility

The process monitoring tool was tested for implementation feasibility at the Concentrator plant. The key test criterion was the tool's ability to derive the EPI based on a valid EPF, and plot it onto the Shewhart chart. After successive observations, the primary mill circuit's economic performance would be assessed based on EPI spread around the historical benchmark, using indicators listed in Table 5-2 .

Table 5-2: Economic performance indicators

Indicator	**Criteria**
Outlier economic performance	One point exceeds UCL or LCL benchmark performance
Runs	Nine points above/below the benchmark performance Four out of five points are above/below the benchmark performance and exceed the $\pm\sigma$ limit. Fifteen points are within the $\pm\sigma$ limits
Good/bad trend	Six consecutive points show continual rise or fall of economic performance indices. Eight consecutive values are beyond the $\pm\sigma$ limits
Periodicity	Defined as economic performance indices showing fluctuating behaviour over time. Difference of consecutive values alternates in sign for fourteen points

Regular re-evaluation of the EPF used to develop the process monitoring tool was important since economic performance functions change within the same process over time (Wei & Craig, 2009c).

5.2.24 Process monitoring post-implementation

With time, good or bad economic performance must be critically reviewed for continuous performance improvement. For example, when high profit is consistently achieved the following questions must be investigated:

1. What changed in the primary mill circuit's operation?
2. Is the change repeatable?
3. Can the change even be enhanced in future operation?

However, answers to the following questions are necessary in the event of a loss:

1. What went wrong or influenced the loss incurred for the primary mill circuit?

2. Is the cause from the preceding question avoidable?
3. What steps can be taken to prevent the loss from recurring?

Figure 5-3 provides a summary of the industrial case study methodology steps.

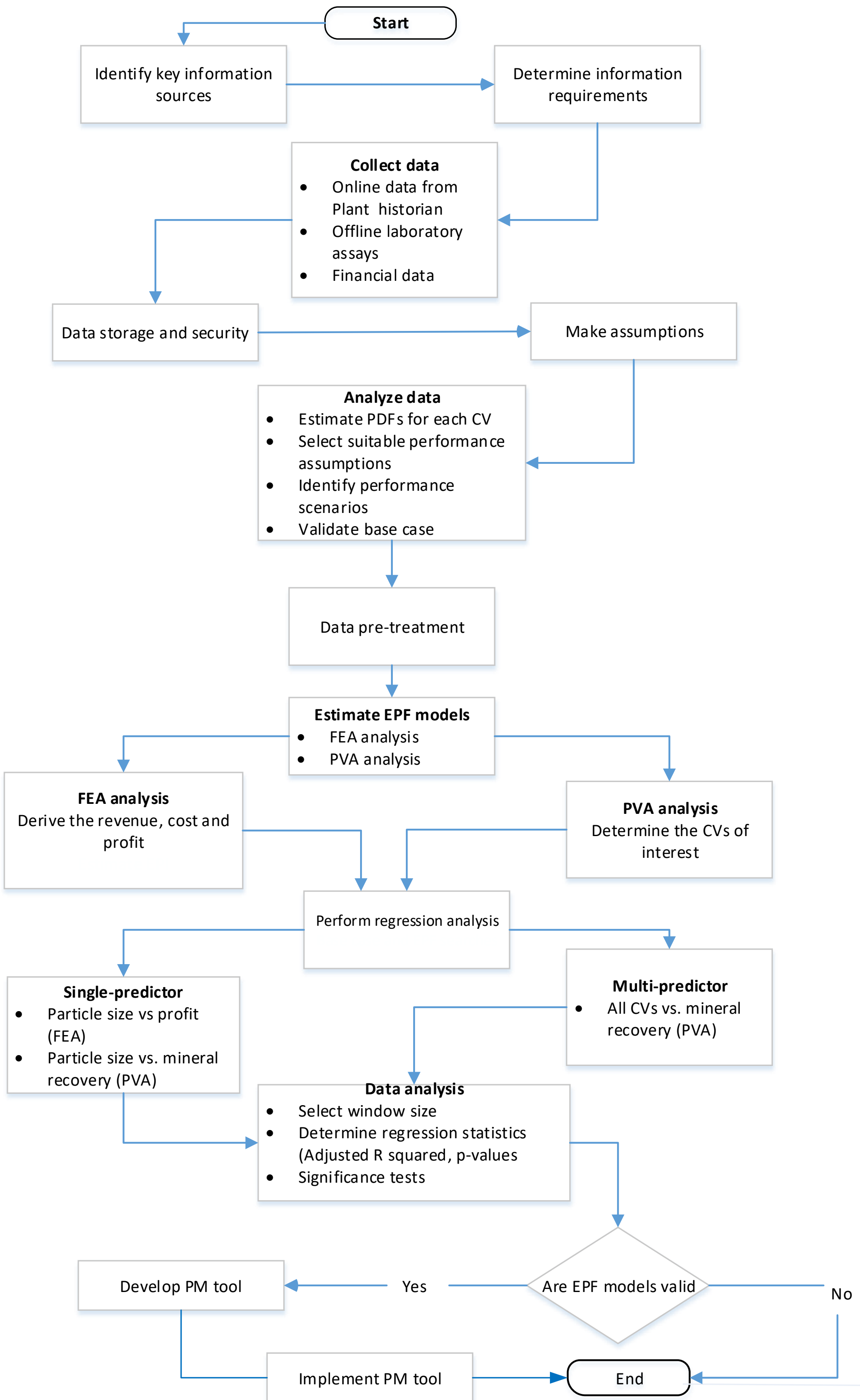


Figure 5-3: Summarized industrial case study methodology steps

5.3 Simulation case study

5.3.1 Objectives

The following objectives were defined for the simulation case study:

3. To derive the economic performance of a SAG mill circuit subject to three common industrial faults; and
4. To assess the economic impact of the fault events and subsequently, determine fault detection feasibility with EPFs.

5.3.2 Simulation case study background

The simulation case study uses typical production and control objectives for a SAG mill circuit, to investigate the economic impact of extreme changes in process conditions, i.e. faults. Faults can result in variable circuit throughput and delivery of inconsistent product particle size (Wills & Napier-Munn, 2006). *A priori* particle size-mineral recovery EPF adopted from Edwards & Vien (1999) was used to evaluate the economic impact of three simulated faults.

The simulation case study offered control over the fault type and sizes, as well as the time window for fault detection. Process recovery in the simulation experiments was effected by PID control. This controller type consists of proportional, integral and derivative tuning parameters that are varied for an optimal response. Reference can be made to Khandalkar, *et al.* (2015) and Wu *et al.* (2015) for more information on this controller.

5.3.3 Overview of the SAG mill circuit

The process description has been presented in Section 1.1.1. The SAG mill circuit is operated to produce at reasonable throughput, a target product particle size from which good recovery can be achieved. In addition, steel ball and electricity consumptions are minimized (Coetzee *et al.*, 2008; Craig & Macleod, 1996; Matthews & Craig, 2013). These objectives require certain trade-offs to be made.

5.3.4 A background to simulation models

Simulation models are widely used to analyse industrial processes, to test several scenarios and investigate effects which are impractical or too expensive to perform on a real process (Hangos & Tuza, 2001). Furthermore, reliable proof of concept results are made available before the investigated concept can be implemented in a real process (Barton, 2013). Simplifying assumptions are often made when simulation models are developed since not all possible situations to which a real plant process is exposed may be simulated. Therefore, models differ in terms of the objective being investigated, which in turn influences the derivation complexity and amount of data required for model calibration (Runge *et al.,* 2007).

5.3.5 Le Roux's SAG mill model

Le Roux *et al.* (2013) validated a nonlinear SAG mill circuit model, which used the least amount of parameters and equations. This model is applicable over a wide operating range and model parameters were fit using steady state data obtained from industrial surveys. Le Roux's model consists of four system volumes in a closed loop SAG mill circuit i.e., the feeder, SAG mill, sump and the hydrocyclone. A perfectly mixed sump volume is assumed, and hydrocyclone dynamics are independent of changes in feed density.

Process streams exist in five states i.e., rocks, solids, fines, steel balls and water. The rocks and steel balls are too large to exit the mill and hence, are consumed in the mill. Solids consist of coarse and out of specification particles that are small enough to be discharged from the mill, while fines are of target specification. Figure **5-4** shows modules and variables for the SAG mill model.

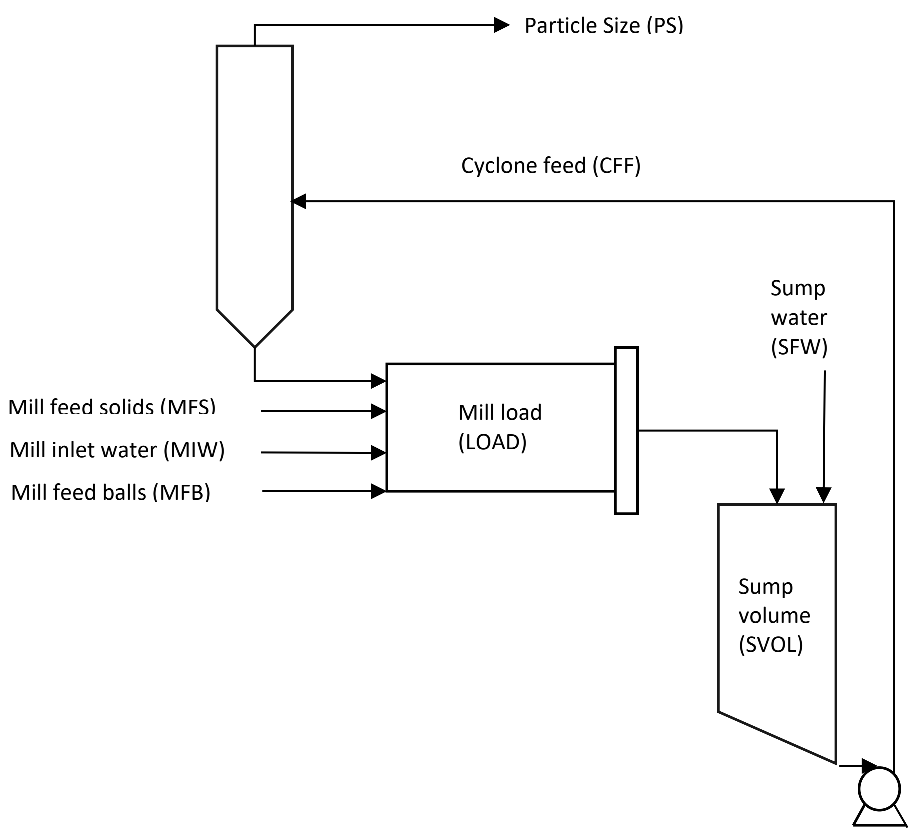


Figure 5-4: Single staged close circuit SAG mill circuit (Adapted from Le Roux *et al.*, 2013)

5.3.6 SAG mill circuit process variables

SAG mill circuit CV-MV control loop pairings are shown in Figure 5-5.

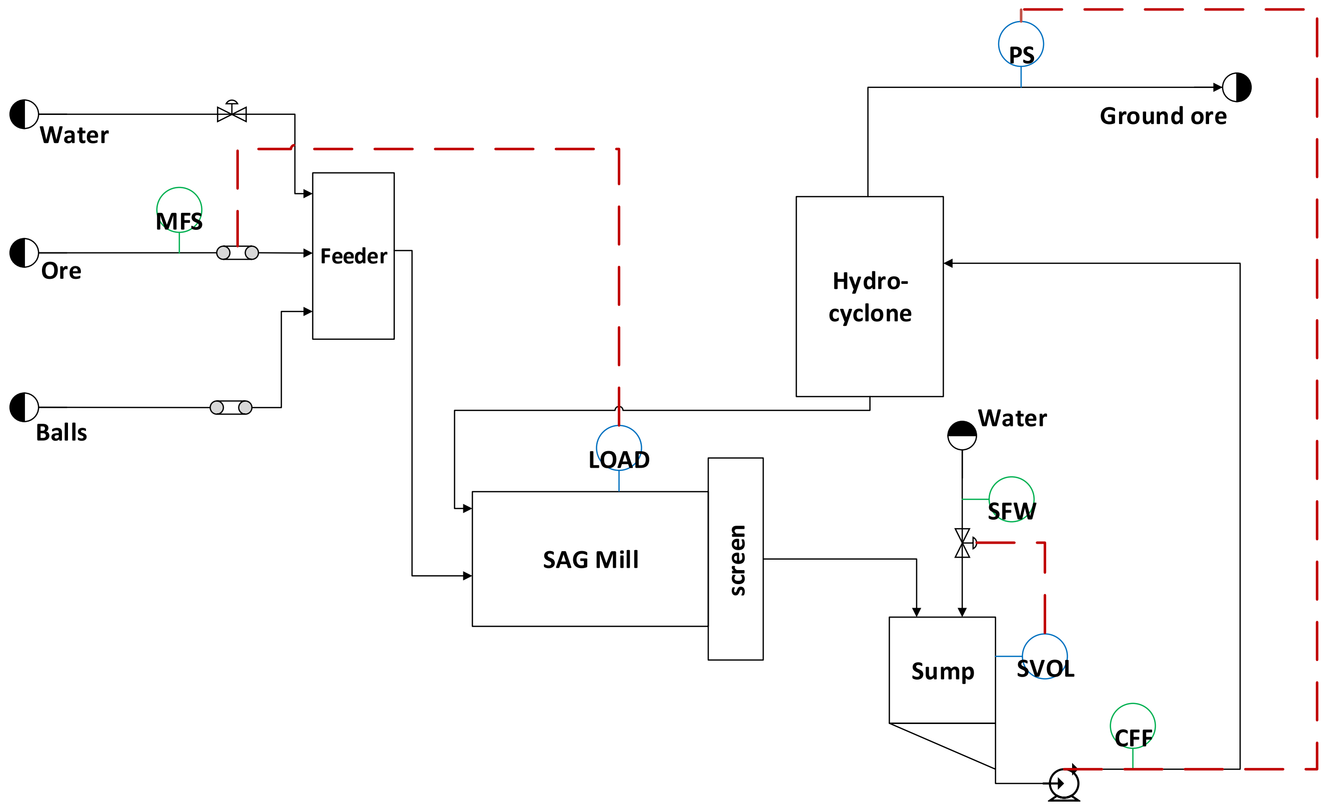


Figure 5-5: SAG mill circuit control loops (Redrawn from Wakefield, 2015)

Table 5-3 lists the CV-MV loop pairings.

Table 5-3: CV-MV loop pairings

Controlled variable	Manipulated variable
Mill volume fill (LOAD)	Mill feed solids (MFS)
sump volume (SVOL)	Sump feed water (SFW)
particle size (PS)	Cyclone feed flow (CFF)

5.4 Simulation case study design

Meaningful simulation results significantly depend on an appropriate experiment design. Poorly planned simulation experiments can give results that provide little insight, or at worst provide misleading results

(Barton, 2013). Therefore, experiments must generate unbiased simulation data that capture the dynamics of the process variables considered. Typically, costly decisions are made based on simulation experiment results. As such, experiments are designed for appropriate data analysis with statistical methods in order to give valid and objective conclusions (Montgomery, 1991).

One key objective for experimental design is to estimate how results are influenced by changes in input factors (Law & Kelton, 1991). To this end, the conditions under which a simulation experiment is conducted, must be well defined. Although simulation experiment conditions depend on the experimenter's goals, there are generic steps for conducting them (Sokolowski & Banks, 2010). Barton (2013) and Leal *et al.* (2011) propose the following steps for experiment design:

1. Define experiment objectives.
2. State a hypothesis to be evaluated.
3. Plan an experiment to test the hypothesis.
4. Conduct the experiment.
5. Analyse experiment results.

These steps were applied in the simulation case study as discussed below. Simulation experiments were conducted in MATLAB's Simulink environment using the procedure proposed by Wei & Craig (2009a).

5.4.1 Defining experiment objectives

The objectives of the experiment were:

1. To derive economic performance indices for three common faults in SAG mill circuits; and
2. To assess the economic impact of each fault.

5.4.2 Stating a hypothesis to be evaluated

The null hypothesis (H_0) tested whether the economic impact of each fault event as represented by the EPI, was indistinguishable to the simulated fault. The alternative hypothesis (H_1) stated that the EPIs (and hence economic impacts) are unique to each simulated fault. The hypotheses are shown in Equation 5-10.

$$H_0 : \mu_{EPI,1} = \mu_{EPI,2} = \mu_{EPI,3} \qquad \text{5-10}$$
$$H_1 : \mu_{EPI,i} \neq \mu_{EPI,j}$$

where the subscripts 1, 2, 3 refer to each of the faults investigated and *i,j* are fault pairs (*i,j* = 1,2,3).

A trade-off exists between mineral recovery and mill throughput, two revenue measures that significantly influence economic performance (Bauer & Craig, 2008). As illustrated in Wei & Craig (2009a), the null hypothesis of these two variables is tested to investigate significant differences between any two simulated faults. Craig & Henning (2000) followed the same approach, albeit for a flotation process.
Equation 5-11 and Equation 5-12 give the null and alternative hypotheses for mineral recovery and mill throughput, respectively.

$$H_0 : \mu_{MR,1} = \mu_{MR,2} = \mu_{MR,3} \qquad \textbf{5-11}$$
$$H_1 : \mu_{MR,i} \neq \mu_{MR,j}$$

$$H_0 : \mu_{THR,1} = \mu_{THR,2} = \mu_{T,3} \qquad \textbf{5-12}$$
$$H_1 : \mu_{THR,i} \neq \mu_{pTHR,j}$$

where the subscripts 1, 2, 3 refer to each simulated fault.

5.4.3 Identifying the significance test

Simulation results were tested for significance using a one-way analysis of variance (ANOVA). Three assumptions are made about the data when this significance test is used. Firstly, simulation experiment data is assumed to be random and statistically independent. Secondly, samples are extracted from normally distributed populations, and thirdly, equal population variances are assumed.

One-way ANOVA is quite robust to deviations from these assumptions (Walck, 2007). Small departures from normality do not significantly affect the results, and for the same sample size, the assumption of equal population variances is not strict. However, it was prudent to investigate the equal variance assumption. The F-test, which is a ratio of sample variances was used to find out whether samples were from the same population. It is performed only when the one-way ANOVA shows a p-value less than the significance level. MATLAB computes F-test statistic based on a null hypothesis of equal population variances. The critical F value ($F^{cv}_{df1,\, df2}$) is determined using F tables and degrees of freedom (df_1 and df_2) corresponding to a significance level (α). The null hypothesis is rejected for $F_{ob} > F^{cv}_{df1,\, df2}$, where F_{ob} is the observed F statistic. If the null hypothesis of equal population variances is rejected, further tests are investigated. However, if the null hypothesis is accepted, then all fault events are from the same population with the same variance.

Further multiple comparison methods i.e., the Tukey-Kramer, Bonferroni and Dunn-Šidák provide pairwise comparisons to determine which means are different. However, the Tukey-Kramer is more preferred as it has greater statistical power compared to other tests and is readily available in computer packages. Moreover, this method is considered the best available for pairwise comparisons when confidence_intervals are needed or sample sizes are not equal for. (Ostertagova & Ostertag, 2013). P-values less than 0.05 indicate with 95% confidence that estimated means for compared faults significantly differ from each other.

Selecting the significance level

Significance levels are rather subjective, but a significance level of α =0.05 is typically used in most experiments. Although, a significance level of 0.01 is used in some cases, it is considered more conservative. The choice of significance level is influenced by the probability of a type I error occurrence where a true null hypothesis is incorrectly rejected. In such cases, a more relaxed significance level may be used as was done by Wei & Craig (2009a) who used α =0.15. To achieve the intended purpose, Craig & Koch (2003) suggested either a marginal increase in the number of replications or relaxing the significance level. This study used a significance level of α =0.05.

5.4.4 Planning an experiment to test the hypothesis

Simulation experiment steps were planned as follows:

1. Introducing process and sensor noise into the SAG mill model
2. Identifying independent, intermediate and dependent variables
3. Identifying common faults in semi-autogenous grinding mill circuits

Introducing process and sensor noise

Process noise was introduced in the SAG mill model using random walks, where a pseudorandom value *x*, was generated with random positive and negative gradients. The gradients were numerically integrated and added to the initial value of the input variable v in v_0 as shown in Equation 5-13 and Equation 5-14 (Wakefield, 2015). This non-deterministic excitation was incorporated in input disturbance variables i.e., the ore hardness and feed size, in order to simulate the dynamic variation seen in industrial data.

$$s_i = \begin{cases} +1, x_i < 0.5 \\ -1, x_i \geq 0.5 \end{cases} \tag{5-13}$$

$$v_M = \sum_{i=1}^{M} s_i \, \Delta t + v_0 \tag{5-14}$$

where the subscripts *i* and *M* denote a step from time 0 to M, respectively.

A fixed sensor noise of 1% was applied to all (mill load, product particle size and sump volume) controlled variable sensors. This sensor noise size is recommended in Castle *et al.* (1984). Applying a fixed size not only simplified the simulation experiments, but also eliminated the likelihood of compromising the quality of simulation results since there was no exact knowledge on typical industrial sizes for relevant sensor noises. To simulate the faster variation common in sensor noise, a higher frequency of 5seconds was used for sensor noise compared to a frequency of 10seconds for process noise.

Identifying and classifying model parameters

All fixed, dependent and independent variables were first identified for the simulation experiments to allow for easier replications. Dependent variables are measures of interest that are not controlled independently, but are affected by independent variable settings. Figure 5-6 shows the controlled (dependent) variables, manipulated (independent) variables, disturbances and simulated faults for the SAG mill model.

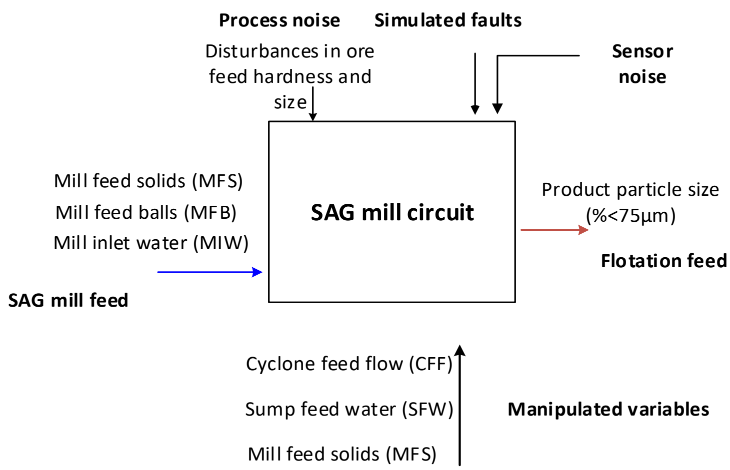


Figure 5-6: Model variables

Selecting experiment design parameters

Appendix L represents mathematical calculations for the SAG mill model. Model parameter input values and initial states were adopted from Wei & Craig (2009a) and Coetzee *et al.*, (2008). Input parameter values were changed accordingly to represent each fault.

Selecting the simulation run length and sampling frequency

Simulation experiments were run for 640 simulation hours to provide a sample size large enough to apportion data into training, test, and fault data sets. This run length was longer than the one to three days recommended by Craig & Henning (2000) for controller simulations. The amount of experiment data generated over the simulation length was sufficient for further classification into eight-hour shifts, to match typical industrial data. A small sampling frequency of 10seconds was used in order to sufficiently capture process dynamics, and generate a large historical data set to satisfy the conditions discussed above.

Identifying simulation faults

Three faults i.e. drifting mill load cell, poor quality steel ball media, and increased ore hardness were investigated for fault detection with EPFs. The faults remained unresolved, except by simulated Proportional-Integral-Derivative (PID) control.

5.5 Conducting the simulation experiments

5.5.1 Simulating the faults

To simulate occurrence after a long processing period, the three faults were each introduced into the simulation run at 400hours. Although the time of fault inception was arbitrarily selected, sufficient time for PID controller action was considered. The effectiveness with which controlled variable set points were maintained in the simulation experiments depended on the capability of corresponding manipulated variables to counteract the faults. Hence, the variability in economic performance was assessed and the differences were contextualised for each fault at a later stage.

A completely randomised design was used for the simulation experiments. This design is appropriate in constant experimenting environments as was the case for this study. The three faults given in Sections 3.4.1 to 3.4.4 were replicated five times each, to give fifteen simulation experiment runs. The experiments were performed following the sequence shown in Table 5-4.

Table 5-4: Randomised simulation experiment runs

1 F_2	2 F_1	3 F_3
4 F_2	5 F_1	6 F_2
7 F_1	8 F_2	9 F_3
10 F_3	11 F_1	12 F_3
13 F_2	14 F_3	15 F_1

where F_i is the fault number for drifting mill load cell (1), poor quality steel ball charge (2), and ore hardness increase (3). According to the resource equation method presented by Mead & Gilmour (1988), the difference between the number of observations and the variables being investigated must typically lie between 10 and 20. The simulation experiment design satisfied this condition.

Drifting load cell

A 45% negative drift was applied over 30minutes to the load cell sensor. In the absence of industrial information on marginal sensor drift sizes, this drift size was iteratively determined based on reaching the mill load constraint over a reasonably short time.

Poor quality steel ball charge

A 60% negative step disturbance was applied to the abrasion factor (φ) in order to simulate poor quality steel ball charge (Appendix M). This step size was reasonably sufficient to simulate rapid steel ball wear.

Ore hardness increase

A 80% positive step disturbance was applied to the ore bond work index to simulate increased ore hardness. This step size was adapted from Wei & Craig (2009a), and is common in industrial operations (Coetzee *et al.,* 2008).

5.5.2 Generating normal operating condition and fault data

For each simulation experiment, normal operating condition (NOC) and fault data were generated for the variables listed in Table 5-5. The NOC data consisted of steady state data with random walk variations, while the fault data was generated from fault inception until the end of a simulation run.

Table 5-5: Simulation experiment data of interest

Controlled variables	- product particle size (PS) - mill load (LOAD) - sump volume (SVOL)
Manipulated variables	- cyclone feed flow (CFF) - mill feed solids (MFS) - sump feed water (SFW)
Other variables	- ore hardness factor - mill load sensor - steel abrasion factor
Cost elements	- mill ball charge (MFB) - mill power draw (P)
Revenue elements	- mill throughput (F) - mineral recovery (MR)

5.6 Analysing the data

5.6.1 Data pre-processing

The PID controller seeks for steady-state conditions as circuit transients persist at simulation run initialisation (Rajamani & Herbst, 1991). This initialisation bias can be a major source of errors when steady state values of system performance measures are estimated (Ghorbani, 2004). Therefore, initial transient phase data is truncated using suitable techniques discussed in literature (e.g., Law & Kelton, 1991; McKinnon & Tipper, 1995; Schruben, 1982). According to McKinnon & Tipper (1995), the Welsh algorithm generates more accurate results for multiple replications as was the case in this study. A manual estimation of when the transient period ends is made after 'n' replications each of length 'm' are generated and an average across the replications is determined. Subsequently, transient phase is visually estimated using a generally conservative approach that deletes a longer duration of the initial transient period (Ghorbani, 2004; McKinnon & Tipper, 1995). Therefore, 10% of the simulation data was deleted as the transient phase data in this study.

5.6.2 Apportioning data into training, test and fault data sets

The data generated from simulation experiment runs were first averaged into eight-hour shifts to resemble typical industrial shift periods. Data were apportioned between training, test, and fault data sets, where the training data set comprised two-thirds of the NOC data and the remaining third made up test data. Fault data constituted of data generated from fault inception until the end of each simulation run.

5.6.3 Selecting bin width

A very large bin width results in loss of data, while a narrow bin width produces few data points in each bin. Thus, the number of bins selected must be sufficiently large to capture major data features while ignoring details due to random sampling fluctuations (Knuth, 2013). Several iterations were performed to determine the most representative bin width for mineral recovery data. Thus, a bin width of 0.05 was identified based on the small data variation and subsequently, used to derive the average potential mineral recovery as discussed in Section 5.7. However, the bin width for processed tonnage was derived using the Freedman-Diaconis (FD) rule for a reasonable number of bins (Equation 20). Similarly, this bin width was used to derive the average tonnage processed.

5.6.4 Making suitable assumptions

The following assumptions were made:

1. The SAG mill product was regarded as flotation feed.
2. The flotation product was sellable product, and was relevantly adjusted to account for costs associated with downstream beneficiation. A value of 0.75 was adopted from Matthews & Craig (2013).
3. The SAG mill circuit was for a PGM operation and industrial unit prices were adopted.
4. A flat industrial rate was assumed for electricity consumption.
5. Only major cost elements associated with operating the SAG mill were considered i.e., steel balls and electricity.
6. Metal basket price, exchange rate and unit cost prices were constant.
7. The costs associated with downstream beneficiation were constant.
8. The quadratic relationship given by Edwards & Vien (1999) was assumed between the product particle size and mineral recovery.
9. All the flow streams to the mill circuit were controllable.

10. The simulation data was normally distributed.

The following data analysis steps were applied for each fault:

5.7 Testing the null hypothesis

5.7.1 Deriving data averages

Mineral recovery data was inferred from the mill product particle size–mineral recovery performance function, and the average potential mineral recovery (PR) was determined using Equation 16 to Equation 19 (Appendix N). Similarly, the average processed tonnage was derived using Equation 16 to Equation 19.

5.7.2 Deriving the sliding window economic performance index (EPI)

Economic performance indices for the training, test, and fault datasets were developed as shown in Appendix N (Equation 21 and Equation 22). A MATLAB algorithm was developed and used to derive the sliding window EPI.

5.7.3 Selecting sliding window size

Process conditions gradually culminate into a fault. Hence, a time-based sliding window size of 10 shifts was selected to analyse simulation data and determine the moving economic performance index. Window sample data were updated in increments of one shift, as the earliest shift was retired.

5.7.4 Plotting sliding window EPIs for all the faults

Sliding window normalized EPIs were plotted onto a Shewhart control chart. The mean EPI derived from normal operating conditions for all the simulation experiments was as the assigned centre line (CL) in the Shewhart control chart. The lower control limit (LCL) and upper control limit (UCL) were determined using three standard deviations.

A null hypotheses of equal economic performance indices, mineral recovery, and mill throughput were tested using one-way ANOVA as discussed in Section 5.4.3 to investigate the significant differences between any two simulated faults. In addition, box plots were constructed for a visual analysis of mineral recovery and mill throughput data for each simulated fault.

5.7.5 Assess scope for fault monitoring and prioritisation

Finally, scope for fault monitoring was assessed based on the detection of faults after each respective fault was introduced in the simulation experiments. Furthermore, scope for fault prioritisation was assessed based on the unique economic impact of each fault, determined from the significant differences between any two simulated faults as discussed in the previous step.

Figure 5-7 shows a summarised methodology flow sheet for the simulation case study.

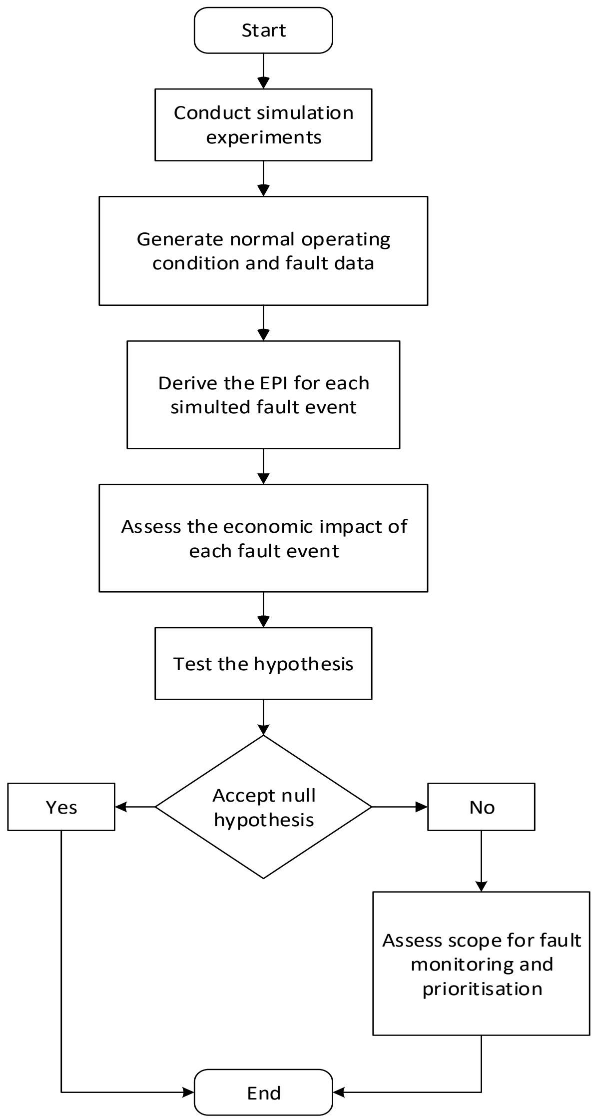


Figure 5-7: Simulation experiments methodology summary steps

Chapter Summary

Chapter 5 presented a research methodology for the industrial and simulation case studies to address the research objectives. The next Chapter presents results and a discussion for the industrial case study.

CHAPTER 6: RESULTS AND DISCUSSION - INDUSTRIAL CASE STUDY

Chapter Overview

The previous Chapter outlined the objectives and methodology steps for the industrial. This Chapter presents industrial case study results and discusses the findings thereof.

6.1 Selection of base-case model data set

Appendix H shows the monthly performance of key indicators between the years 2012 and 2016. All the KPIs showed variability across the years, to correspond with changes in operating conditions such as feed ore properties and management decisions on throughput targets. The annual performances are each summarised in Table 6-1.

Table 6-1: Key performance metrics

Key performance metric	Years				
	2012	2013	2014	2015	2016
Electricity per ton milled			√		X
Production cost per ton milled			√		X
Tonnage processed	X				√
3E rougher flotation recovery	√		X		
Profit/ton			X		√

Key: **X** worst performance √ best performance

In Table 6-1, the years 2014 and 2016 each show two best and two worst cases across the years reviewed. The year 2012 shows a best and worst case for the performance metrics considered. However, the years 2013 and 2015 are intermediate as none of the performance metrics are either best or worst cases. Therefore, they are both suitable candidates for base-case performance scenarios. Although base-case data could be selected from either year, a recent processing period with stable operation was more favourable. Subsequently, the year 2015 was selected and data equivalent to two months (September – October 2015) were adopted for the base-case profit benchmark. Data for benchmark validation cases (best, base and worst) was derived using the data shown in Table 6-2.

Table 6-2: Data for benchmark validation cases

Case	Month	Year
Best	January	2016
Base	February	2015
Worst	August	2014

Data selected for validation cases were supported by the monthly profit per ton plot shown in Appendix H. The normalized profit/ton for the benchmark and the three cases was derived and plotted as shown in Figure 6-1.

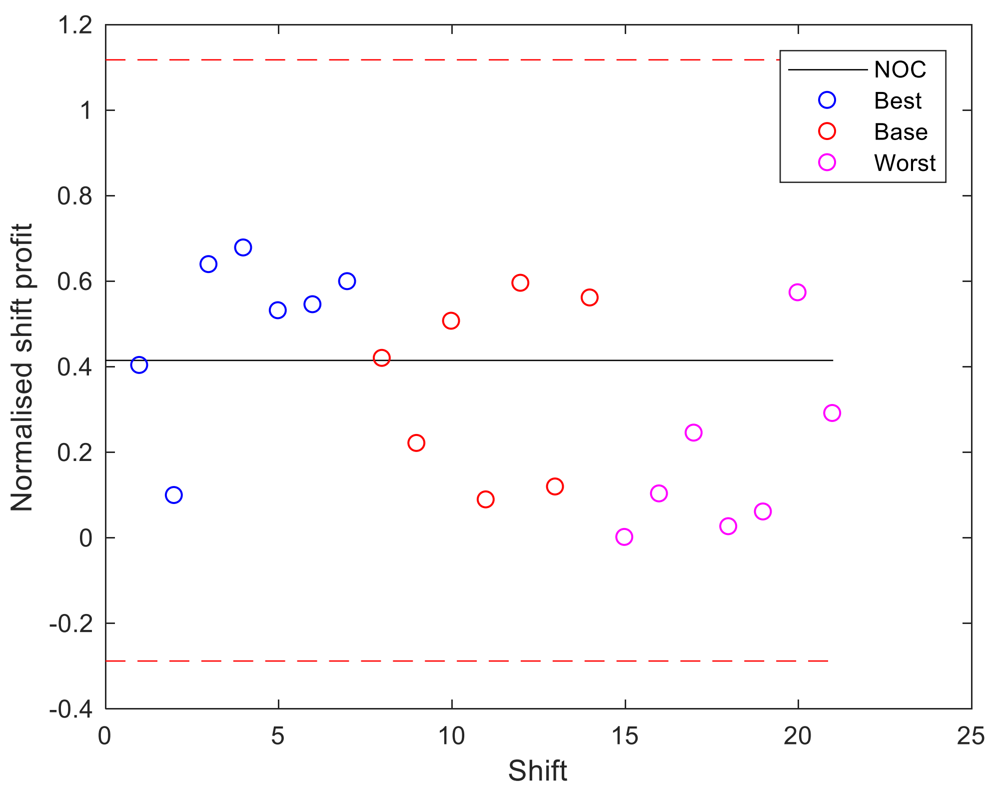


Figure 6-1: Profit for base-case benchmark and performance scenarios

As expected, most of the best-case profit i.e. 71% of the 7shifts lies above the base-case benchmark, and 86% of the 7 worst case shift profit lie below the base-case benchmark. The test base-case shift profit is evenly distributed around the selected benchmark. Thus, the selected benchmark was validated for further use in the process monitoring tool.

6.2 Data normality

Q-Q normality probability plots for the base case model variables are shown in Figure 6-2.

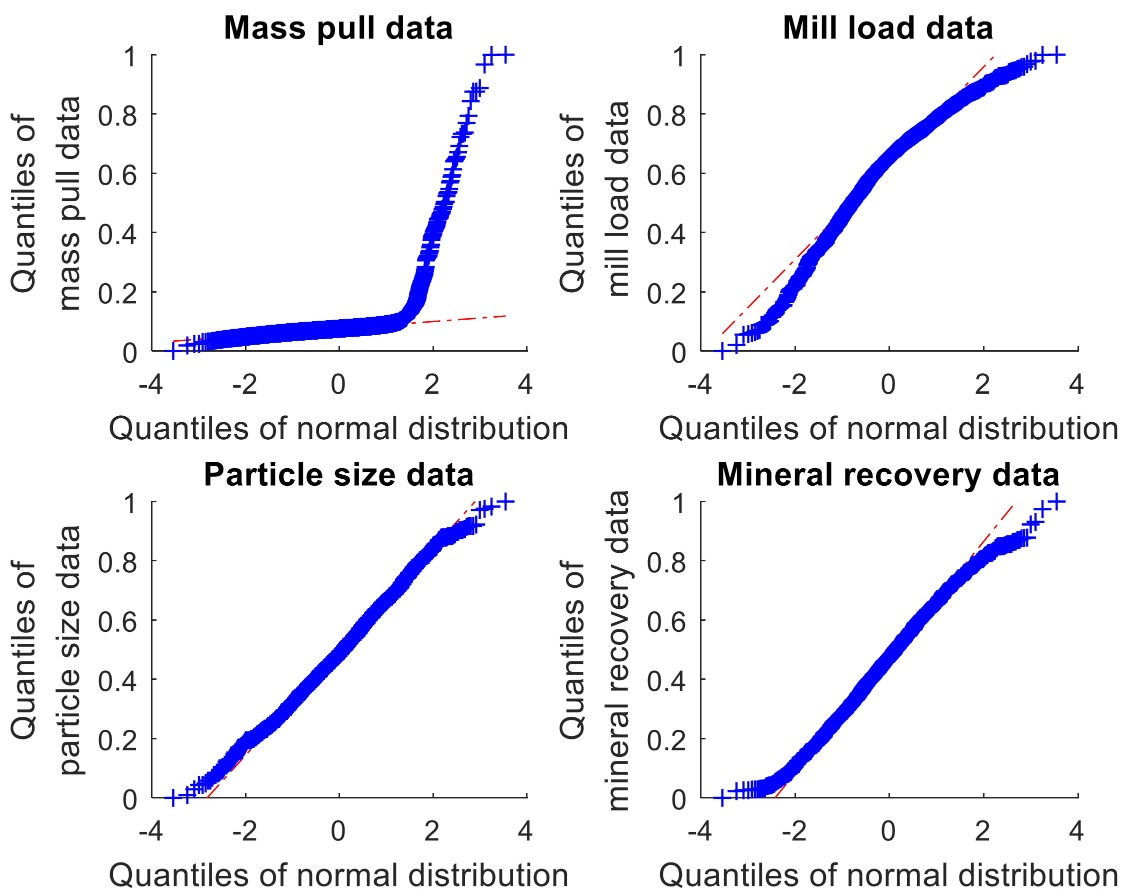


Figure 6-2: Q-Q normality probability plots

With process control, distributions for CV data differ between variables controlled around a set point (normally distributed) and as close to a set point as possible but not exceeding the set point (skewed distribution). Rougher flotation mass pull is regulated to attain the set-point and consequently, stabilise concentrate flow such that liberated minerals are recovered. Hence, mass pull data shows a positive skew (Figure 6-2). However, mill load data show a negative skew since it is operated close to the maximum constraint. Particle size and mineral recovery data show very little departure from normality. Therefore, the normality assumption is valid for all the variables.

6.3 Data correlation

Correlations for filtered data were investigated with scatter plots as shown in Figure 6-3. The data is normalised in order to mask industrial information.

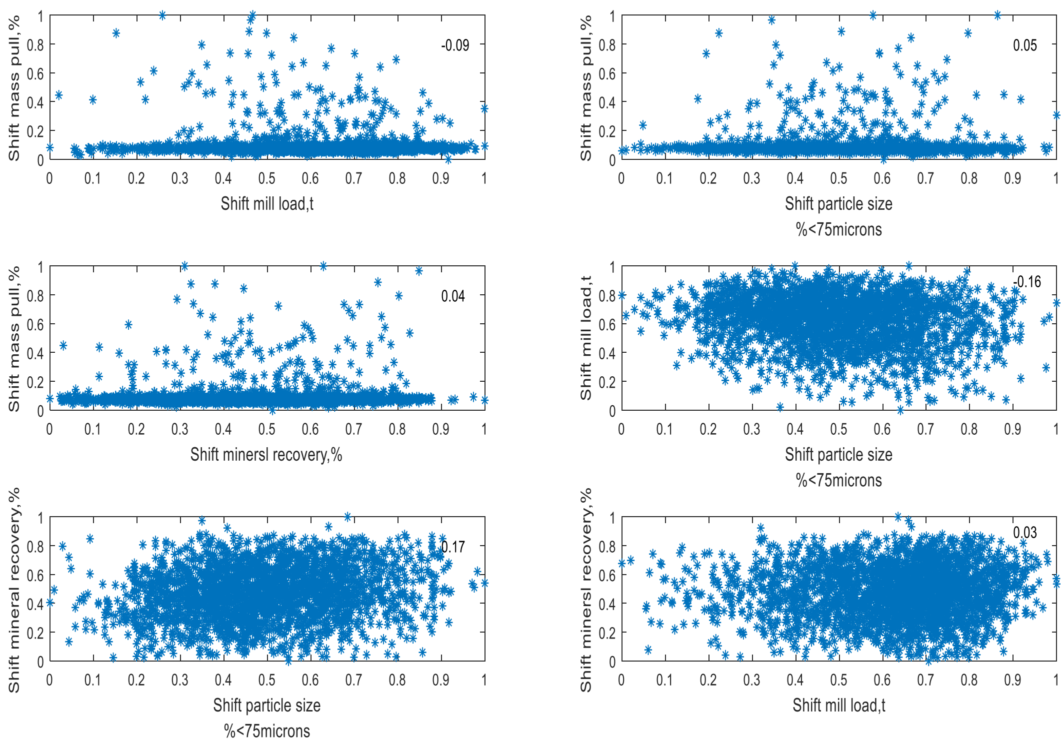


Figure 6-3: Scatter plots for filtered regression model data

Primary mill circuit variables are known to have multiple and often unexplained interactions (De Haas, 2012; Wills & Napier-Munn, 2006). However, this does not appear in any of the scatter plots. Instead, weak correlations are shown for all variables. The likely reasons for weak correlations between the particle size and mineral recovery are discussed in Section 6.4.3.

A well performing model predictive controller (MPC) determines the set of input variables that maintain process variability at a minimum and as close as possible to set points, whilst satisfying manipulated variable constraints. This is observed for mill load, which is tightly controlled close to the maximum constraint. Mineral recovery improves with mass pull but a trade-off exists between the mineral recovery and concentrate grade, should the mass pull continue to increase. However, a weak correlation is observed between the two. Laboratory tests conducted at the Concentrator showed that an increase in mass pull beyond 5.5% resulted in minor overall recovery increase. This may explain the erratic variability beyond the mass pull of 10%.

The data variability observed in Figure 6-3 was initially considered as suitable for reliable EPF model development. However, the correlation coefficients were too weak for meaningful relationships to be developed amongst variables. The weak correlations may have been due to process interactions that are introduced by recycle flows, resulting in measurement lags.

6.4 Single-predictor EPF results

6.4.1 Single-predictor PVA model

Figure 6-4 shows a particle size-mineral recovery (PS-MR) EPF developed with the base-case training data set, and **Table 6-3** summarises results for the model.

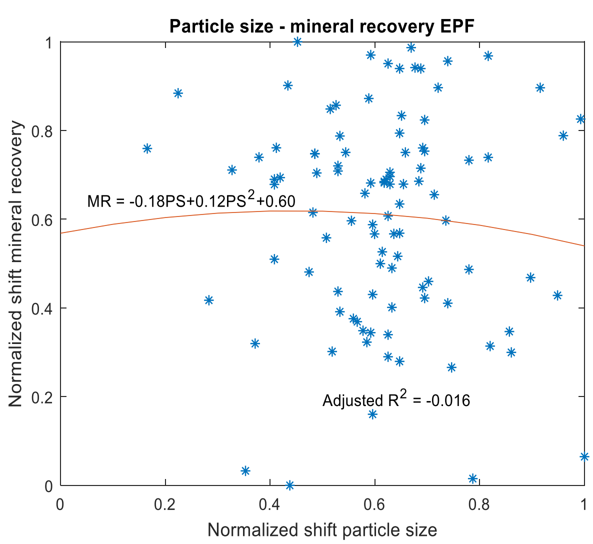


Figure 6-4: Particle size-mineral recovery

Table 6-3: Single-predictor PVA

Single-predictor PVA model	
R^2_{adj}	-0.016
Missing data	0
Outlier 1	0
Outlier 2	0
Negative outliers	0

An R^2_{adj} value of -0.016 indicated poor model fit between particle size and mineral recovery data, such that no significant relationship could be developed between the two. No outliers or missing data were present in the training data set analysed (Table 6-3).

6.4.2 Single-predictor FEA model

Figure 6-5 shows the particle size-financial profit (PS-P) EPF, and Table 6-4 summarises results for the model.

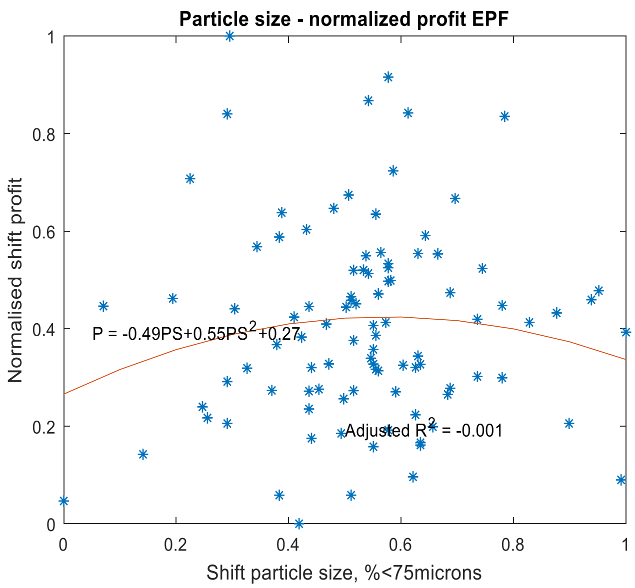


Figure 6-5: Particle size-financial profit EPF

Table 6-4: Single-predictor FEA results

Single-predictor FEA model	
R^2_{adj}	-0.001
Missing data	0
Outlier 1	1
Outlier 2	1
Negative outliers	0

An R^2_{adj} value of -0.001 pointed to poor mode fit between particle size and profit data. Consequently, no good predictions could be made with this model. No missing data were identified in the training data set. However, two outliers were present in the data (Table 6-4).

6.4.3 Results summary for the single-predictor EPF models

The results obtained using both FEA and PVA approaches contradict *a priori* knowledge on the particle size-profit function relationship. Grind improvement typically improves the profit function, subject to an optimal grind which results in a drop in grade when exceeded. Therefore, the particle size-profit function EPF was expected to describe a quadratic function. However, this was not so, due to poor model fit.

The primary mill is operated with the key objective to maintain a constant product size at maximum throughput. As such, the particle size was expected to normalize at a particular throughput to give a consistent grind, but this is not seen in any of the plots (Figure 6-4 and Figure 6-5). Giddy (1988) attributed this occurrence to the throughput maximisation objective of primary mills. Unlike secondary or regrind mills which are operated to achieve the desired fineness of grind, primary mill operation is more concerned with processing high tonnages than getting the correct particle size. Therefore, Giddy (1988) noted that erratic grind results often characterize primary mill operation. An internal report by Johannesburg Consolidated Investment Company Limited (1980) on the erratic behaviour between the ore grind and rougher flotation mineral recovery for the industrial operation supported these findings

The long sampling frequency of particle size and mineral recovery assay data were likely an additional limitation. Important in-between events may have been missed and the true dynamics not well reflected in the shift data. Consequently, the developed single-predictor EPF models were unsuitable for making performance predictions and for the industrial process monitoring tool.

6.5 Multi-predictor EPF results

A model between key CVs (mill load, sump density, mass pull, and particle size) and mineral recovery was also developed. Table 6-5 and Table 6-6 summarise PVA and FEA results, respectively.

6.5.1 Multi-predictor PVA model

Table 6-5: Multi-predictor PVA results

Multi-predictor PVA	
R^2_{adj}	0.0083
Missing data	0
Outlier 1	0
Outlier 2	0
Negative outliers	0

The multi-predictor EPF model had an R^2_{adj} of 0.0083 to signify poor model fit. There were no missing or outlier data.

6.5.2 FEA model with multiple predictors

Table 6-6: Multi-predictor FEA

Multi-predictor FEA	
R^2_{adj}	-0.0524
Missing data	0
Outlier 1	1
Outlier 2	1
Negative outliers	0

The multi-predictor EPF model had an R^2_{adj} of -0.0524 to signify poor model fit. There were no missing data, however, two outliers were identified in the base-case training data set.

6.5.3 Results summary for multi-predictor EPF models

Both multi-predictor FEA and PVA models had poor fit, and hence no performance predictions were made. Thus incorporating more controlled variables did not improve the models as R^2_{adj} values remained below the threshold.

6.6 Findings for EPF model development with base-case data

The EPF models developed with base-case training data gave insight into some aspects that were addressed in the subsequent investigation. A point in case was the difficulty to identify a conventional quadratic relationship between the particle size and profit function. Although Giddy (1988) cited the operating objective of the primary mill as a key limitation, the likelihood of dynamic steady states was another plausible limitation, which was overcome by searching for EPFs throughout the historical data.

6.7 EPF searches

Single-predictor and multi-predictor PVA results are presented for EPF searches with a window size of 42shifts.

6.7.1 Single-predictor PVA models

After outlier deletions were made, 43% and 54% of the particle size and mineral recovery data respectively, were missing. Figure 6-6 shows normalized window mean particle size, standard deviation and relative standard deviation (RSD) for the product particle size.

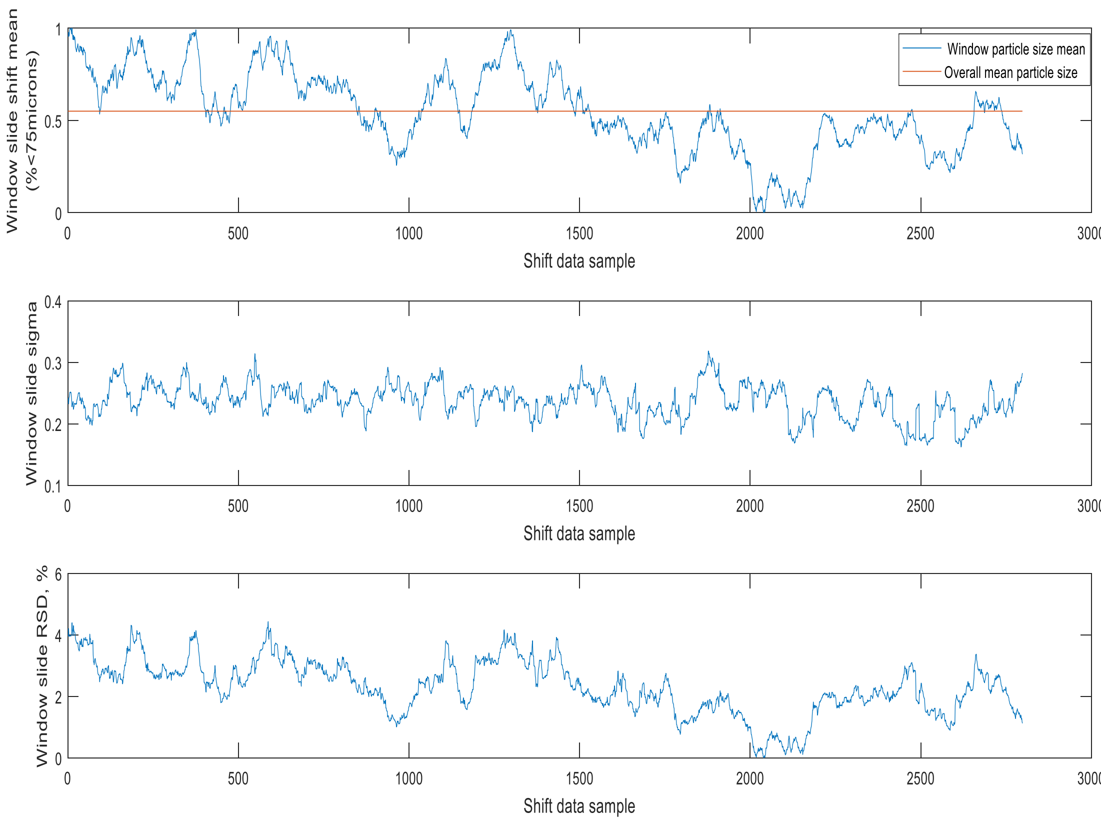


Figure 6-6: Particle size moving window statistical data

Window mean particle size shows a persistent below mean trend after 1500 window slides. Variability within each window slide is observed for the standard deviation data, and the RSD plot shows particle size variability across window slides. High variability is observed between 2000 to 2500 window slide shifts, relative to the first 1500 window slides. The least variability is observed between 500 to 1000 window slides. Hence, the observed trends show some variability which is necessary for EPF model development.

Figure 6-7 shows plots for normalized mineral recovery window mean, standard deviation, and RSD.

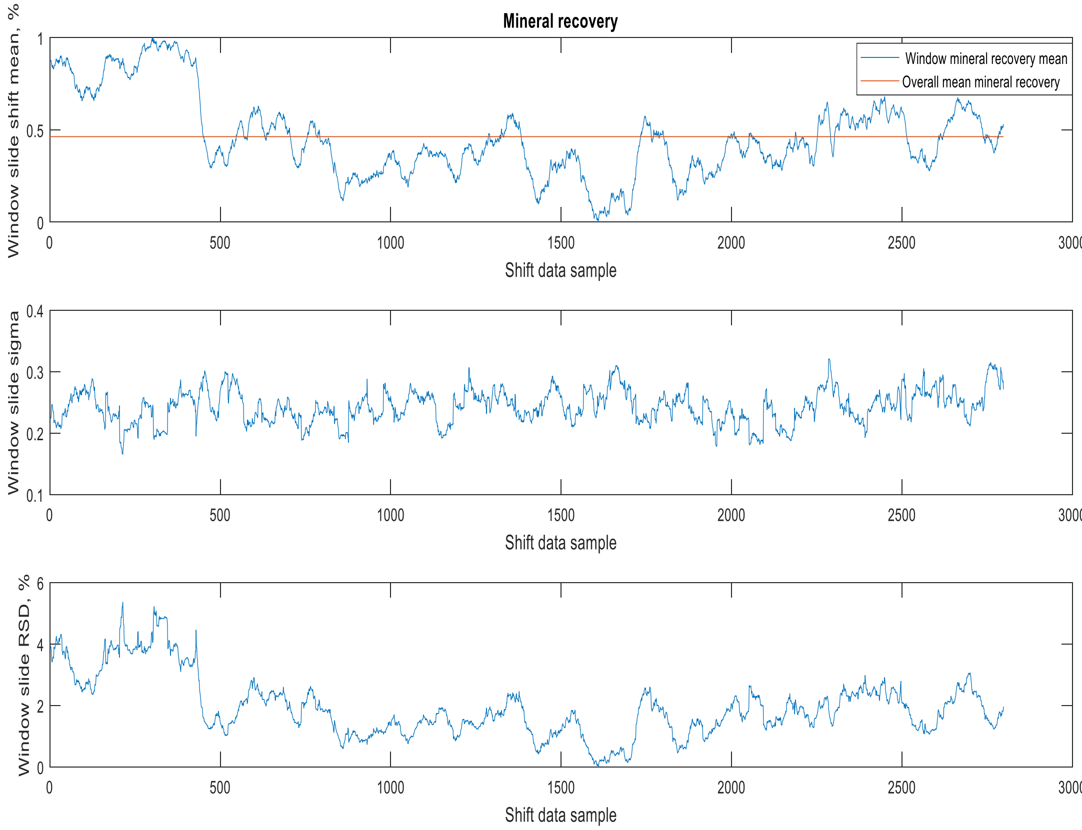


Figure 6-7: Mineral recovery moving window statistical data

The first 500 window slides show high mineral recovery means. High window data variability is observed for the window slides 2000 to 2500 in the standard deviation plot. The RSD plot shows high variability within the first 500 window slides.

Figure 6-8 shows window slide $R^2_{adj,actual}$ (actual data) and $R^2_{adj,test}$ (test data in a consecutive window) for single-predictor EPF models.

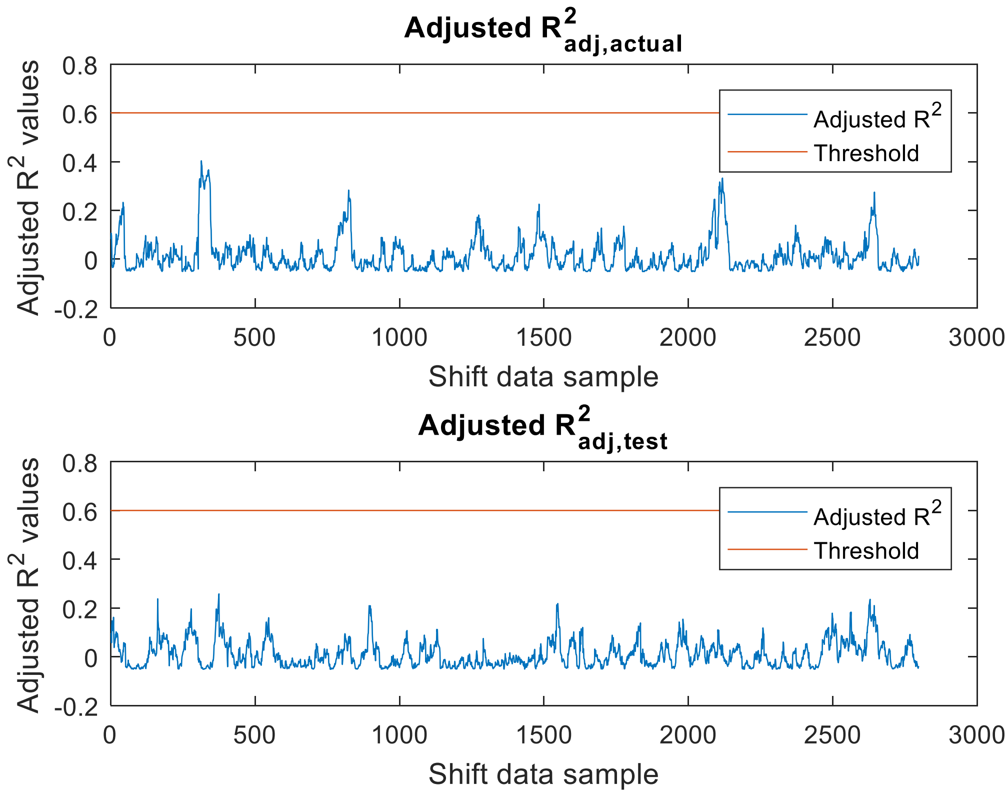


Figure 6-8: Single-predictor PVA adjusted R-squared values

All R^2_{adj} values fall below the threshold and therefore, have poor model fit for both the actual data and investigated measurement lag. Figure 6-9 shows normalized actual and predicted mineral recovery plots for each window slide.

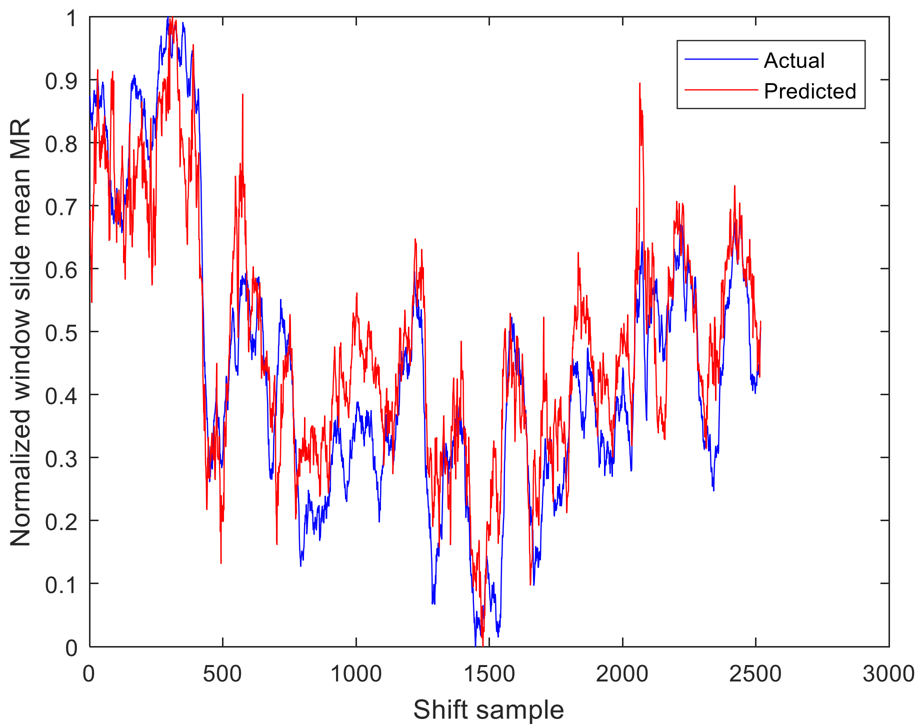


Figure 6-9: Normalized actual and predicted mineral recovery for single-predictor EPF models

The similar trends between predicted and actual mineral recoveries in Figure 6-9 are investigated for any significant difference. A plot of the actual vs predicted mineral recovery is shown in Appendix O.

Table 6-7 presents a summary of single-predictor PVA results.

Table 6-7: Single-predictor PVA summary results

Single-predictor PVA	
Maximum $R^2_{adj,actual}$	0.58
Maximum $R^2_{adj,test}$	0.50
$R^2_{adj,actual}$ >0.6	0
$R^2_{adj,test}$ >0.6	0
Missing MR data	54.4%
Missing PS data	42.5%
Outlier 1	11
Outlier 2	1
Negative outliers	0

Although single-predictor EPF models developed with actual and test data had poor model fit, the maximum R^2_{adj} for actual data was better. The model data had 12 outliers but no negative values. For window size 21shifts, the SP approach did not have above-threshold EPF models for both actual and test data (Appendix P).

6.7.2 Multi-predictor PVA results

Table 6-8 presents the amount of missing data for each primary mill circuit variable.

Table 6-8: Missing data

Variable	**Missing data (%)**
Mass pull	1.81
Mill load	0.61
Mill density	51.1
Particle size	22.9
Mineral recovery	30.4
Overall missing data	69.2

The mill load recorded the least amount of missing data, while the mill density had 51.5% missing data and this was the highest amount recorded. As a result, data constituting of 69.2% were missing and consequently, only 30.8% complete vectors. The overall amount of missing data reduced to 38.6% when mill density data were excluded. Therefore, 61.4% of the data were available for reasonable EPF model development.

Window mean, standard deviation and window relative standard deviation for particle size and mineral recovery have been highlighted in Figure 6-6 and Figure 6-7, respectively. Figure 6-10 shows mass pull window data.

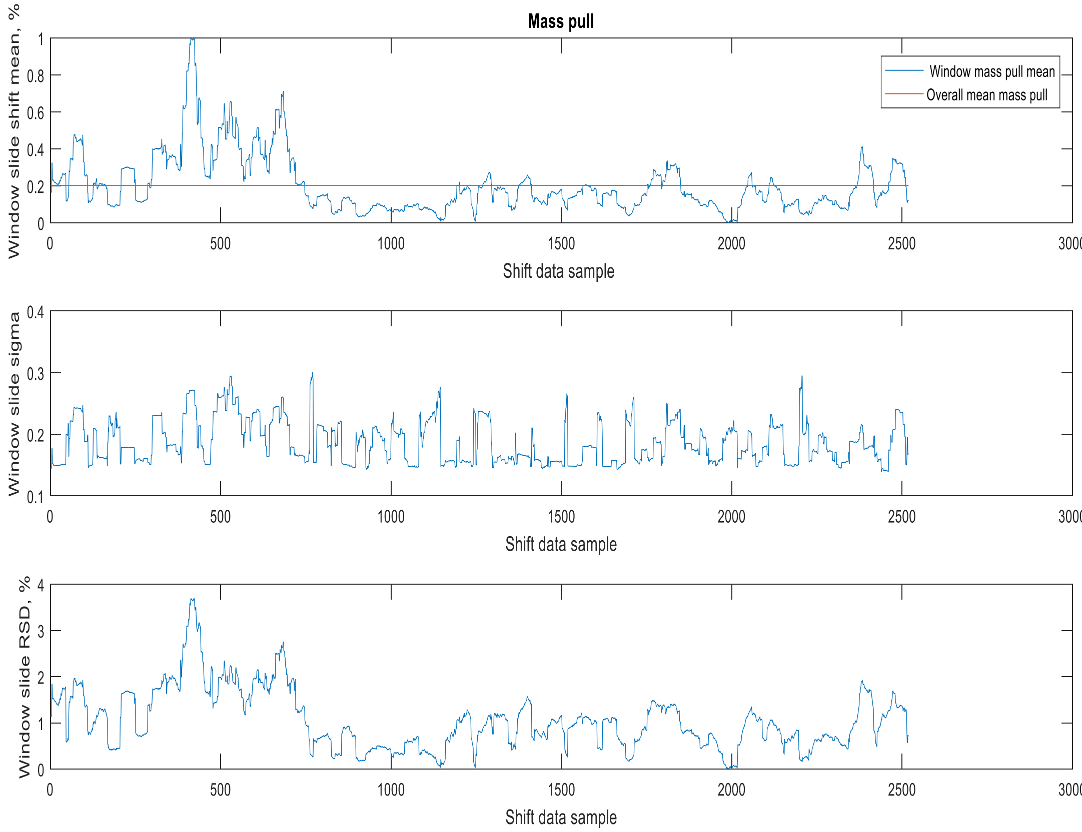


Figure 6-10: Mass pull moving window statistical data

Most of the mass pull mean data within the first 1000 window slide shifts lies above the overall mean. The high mass pull suggests maximum mineral recovery, and this is observed in Figure 6-7. Therefore, the two are well correlated. The RSD plot shows significant variability in mass pull data across the window slides. Figure 6-11 shows a plot for the mill load window data.

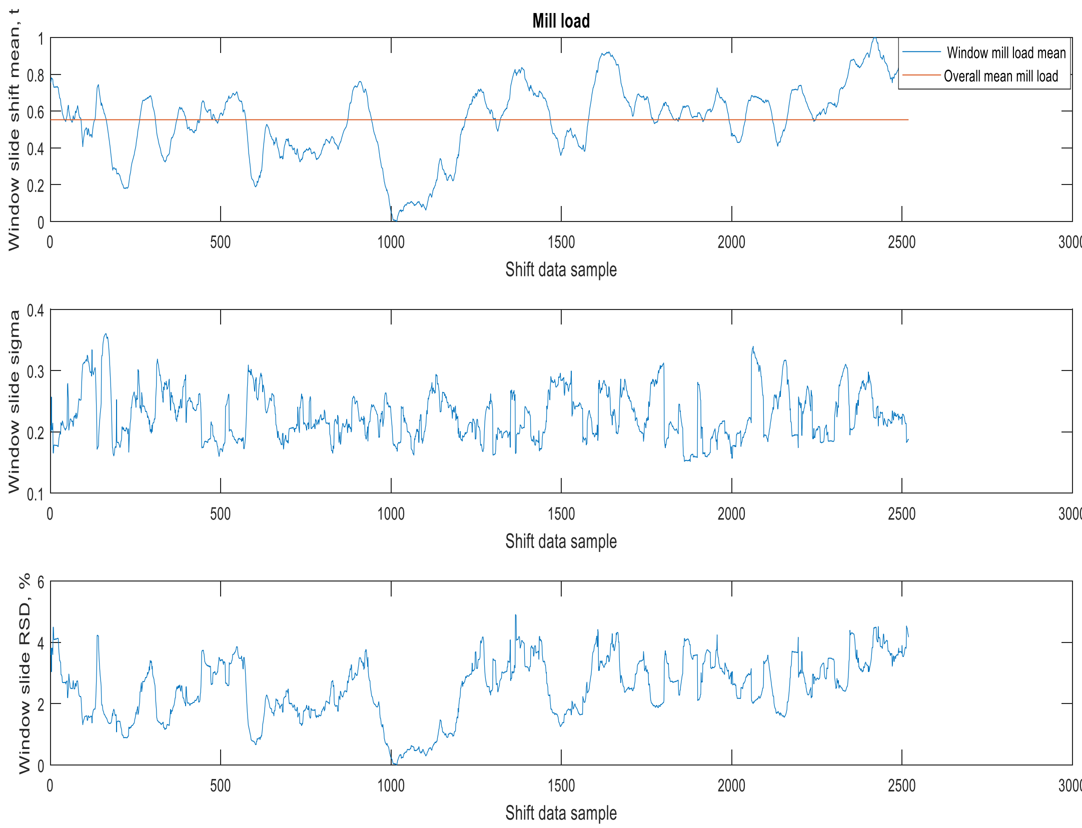


Figure 6-11: Mill load moving window statistical data

The window means do not show any obvious distributions around the overall mean as the mill load is tightly controlled around the set point. However, the standard deviation plot shows some variability within window slide data. The RSD plot shows a wide variability across the window slides of between 20 and 100% as a result of the changes in mill load set point to accommodate tonnage increments across the years.

Figure 6-12 shows the R^2_{adj} plots for the actual and test data.

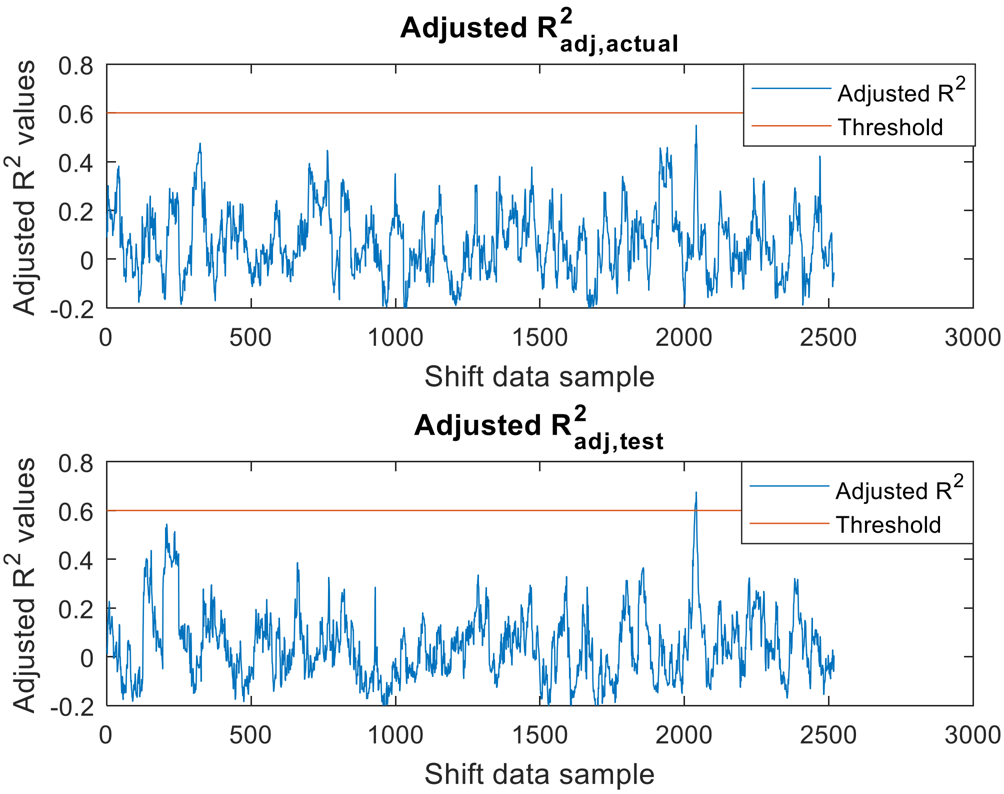


Figure 6-12: Multi-predictor PVA adjusted R-squared

$R^2_{adj,actual}$ values in the first plot fall below the threshold value, to indicate poor model fit. However, six $R^2_{adj,test}$ values in the second plot lie above the threshold. These six models were restructured to only consist of significant regression coefficients. As a result, only four of the six models had significant coefficients. Figure 6-13 shows the $R^2_{adj,test}$ for each of the four EPF models, where y - mineral recovery, x_1 - mass pull, x_2 - mill load, and x_3 - particle size. R^2_{adj} values for all four models fall below the threshold.

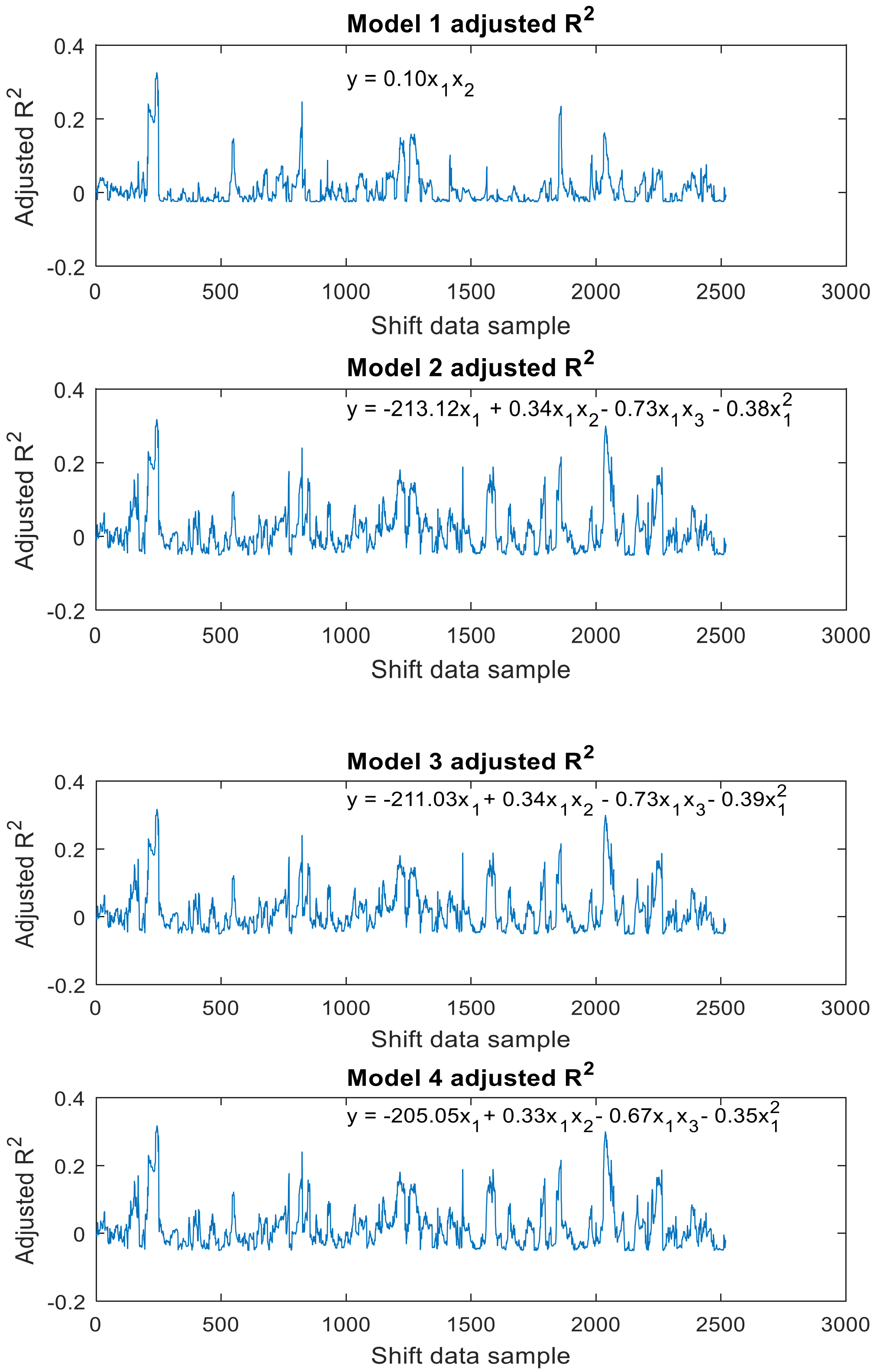


Figure 6-13: Adjusted R-squared values for reduced EPF models

The four models appeared in consecutive window slides and the relative standard deviation for each model is shown in Figure 6-14.

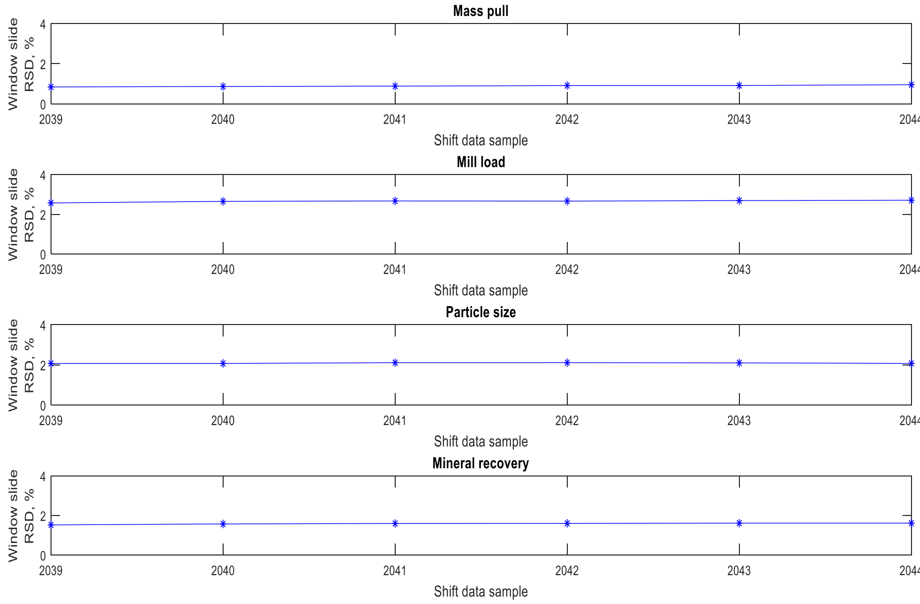


Figure 6-14: Models with above threshold R^2_{adj} and significant regression coefficients

In Figure 6-14, the data shows very little variability and hence, may explain the above-threshold R^2_{adj} values obtained for the four models. Normalized actual and predicted mineral recovery values were plotted (Figure 6-15) in order to further investigate the validity of these models.

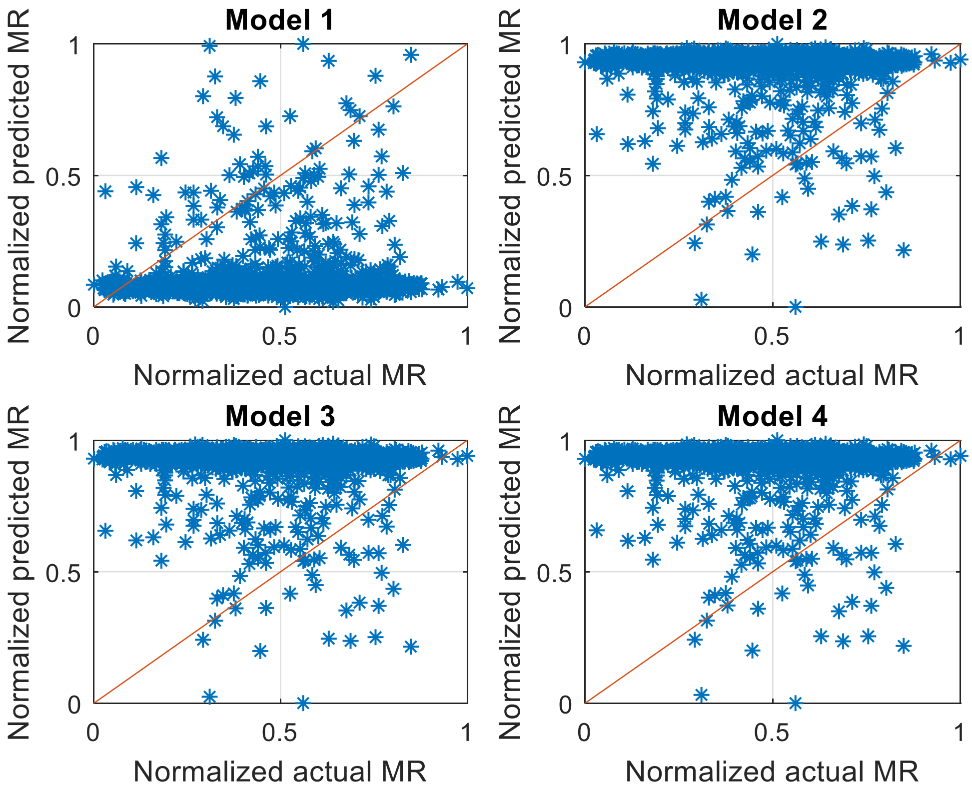


Figure 6-15: Actual and predicted mineral recovery

The plots show poor model predictions of actual mineral recovery and hence, the models were invalid. Summarized results for multi-predictor PVA analysis are presented in Table 6-9.

Table 6-9: Multi-predictor PVA summary results

Multi-predictors' PVA	
Maximum $R^2_{adj,actual}$	0.53
Maximum $R^2_{adj,test}$	0.67
$R^2_{adj,actual} > 0.6$	0
$R^2_{adj,test} > 0.6$	6
Outlier 1	11
Outlier 2	2
Negative outliers	199

Appendix P shows $R^2_{adj, train}$ and $R^2_{adj, test}$ results for a window size of 21 shifts. The results show some evidence of overfitting as 57 and 41 models had above-threshold R^2_{adj} values for actual and test data, respectively. Therefore, a window size of 21shifts was too small to develop meaningful EPF models.

6.7.3 Results summary for EPF searches

Based on the successful development of an EPF between particle size and mineral recovery at laboratory scale, it was expected that reliable EPF models could also be developed with industrial data. However, the results obtained in this study demonstrated difficulty to develop EPF with industrial data. A significant amount, i.e. 61% of the industrial data was assessed and showed good variability. Although good correlations were expected between data, none of the variables had significant correlation coefficients. Furthermore, the quadratic relationship between particle size and mineral recovery data remained elusive due to the limitations highlighted in Section 6.4.3.

While no reliable EPF models could be developed, four of the models developed with the multi-predictor approach showed $R^2_{adj,actual}$ values above a threshold of 0.6.

6.8 Summary results for EPF development strategies

Results for base-case data and searches for EPFs strategies demonstrated better results with the latter strategy. EPF searches were more effective relative to EPF development with base case data, based on achieved R^2_{ajd} results. Hence, the assumption of dynamic steady states seemed to hold. However, both strategies showed poor model fit.

Due to bias and data distortion risks associated with case reweighting or multiple imputations, either option was not considered in this study. R^2_{adj} values for test data were better, compared to training data results. The difference was more pronounced for the multi-predictor PVA approach where an R^2_{ajd} of 0.58 against 0.67 was obtained for actual and test models were obtained, respectively. This showed better correlation between mineral recovery data and controlled variables for the next window, pointing to possible measurement lags in some of the controlled variable.

The data variability observed in scatter (Figure 6-3) and RSD plots (Figure 6-6, Figure 6-7, Figure 6-10, and Figure 6-11) appeared to be sufficient for EPF development. However, the poor results suggest inadequate variability for EPF development, due to robust model predictive controller action. In addition, process variable dynamics were smoothed out by using shift composite samples to analyse particle size and mineral recovery. Therefore, the shift averages did not adequately capture the process dynamics. As a further limitation, some important in-between events were lost due to deletions made during data cleaning. For example, in cases where one variable had fault data, corresponding data in other variables was also deleted to preserve the relationships between variables. However, doing this inevitably reordered data sequencing and disturbed the time series effect.

Due to the highlighted limitations, it was not possible to develop a reliable EPF model with industrial data. Consequently, the process monitoring tool could not be implemented at the industrial operation.

Chapter Summary

Chapter 6 presented industrial case study results. Two approaches i.e., FEA and PVA were investigated for single and multi-predictor EPF model development using two strategies i.e., base case data and searches for EPFs throughout the data. It was difficult to develop a reliable EPF for either for cases as results characterized poor model fit. Furthermore, the quadratic relationship between particle size and mineral recovery remained elusive throughout historical data. Some evidence of measurement lags, information loss due to reordered data sequences and data cleaning techniques, erratic particle size data due to a throughput maximisation objective, and robust controller action emerged as possible key limitations.

The next Chapter discusses simulation case study results.

Chapter 7: Results And Discussion - Simulation Case Study

This Chapter reports on the economic impact of three simulated faults - drifting load cell, poor steel ball quality, and increased ore hardness.

7.1 Controlled variable –manipulated variable plots for simulated faults

7.1.1 Drifting mill load cell

CV-MV plots are shown in Figure 7-1 for a mill load cell with negative drift. All the plots show truncated transient-phase shifts.

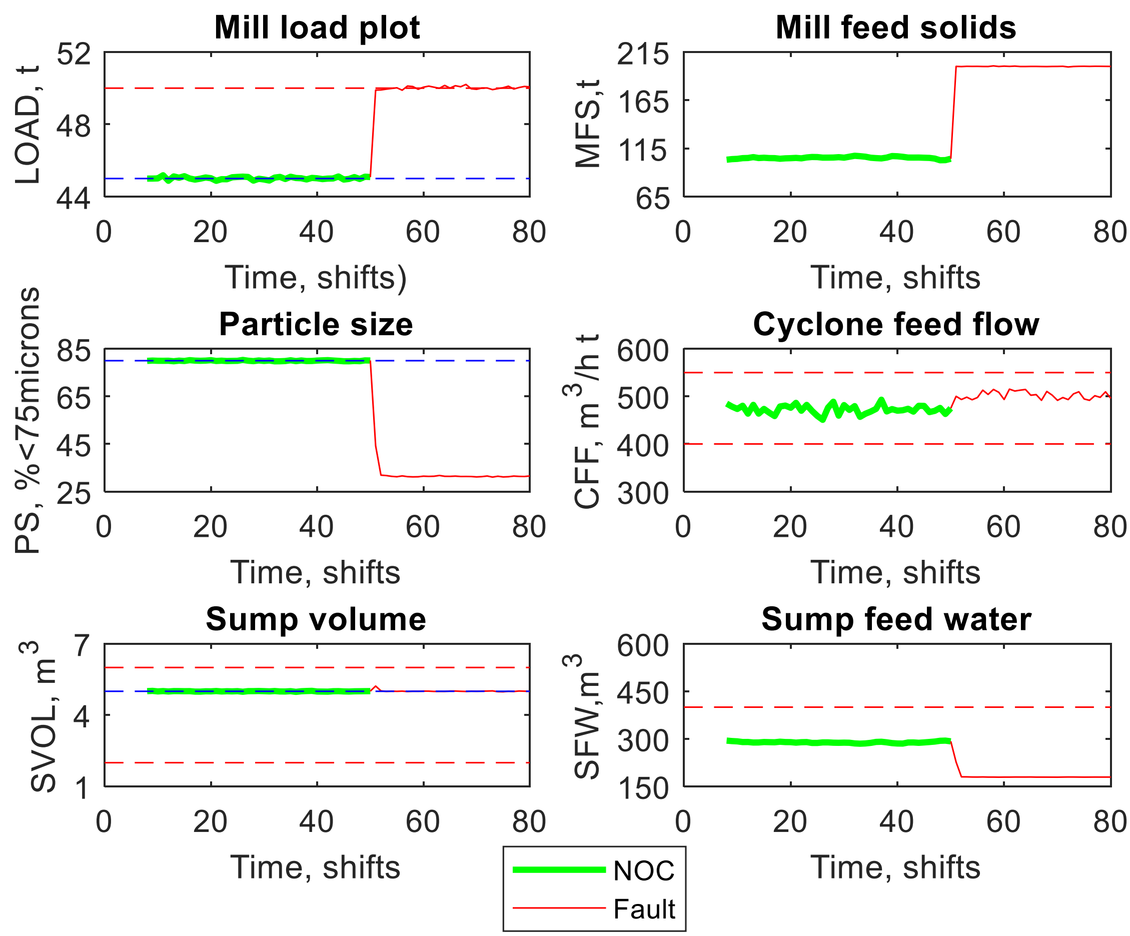


Figure 7-1: CV-MV plots for drifting mill load cell

At fault inception, the mill load gradually increased until it reached saturation level. Mill feed solids increased to correspond with the change in mill load, based on modelled equations. In industrial operations, mill discharge rate typically increases at high mill loads to stabilise the mill load (Wei & Craig, 2009c). The load cell drift was propagated to the particle size, which dropped by about 54% to give a coarse product. As a result of poor in-mill trajectories arising from an increased mill feed solids rate, the product particle size did not improve within the simulation run length. However, the 5% increase in hydrocyclone feed flow implied an increase in coarse material recirculation for further grinding. The PID controller maintained the sump volume around the set point to minimize circuit instability. Consequently, the sump feed water flow rate reduced in order to maintain the sump volume, since the mill discharge flow had increased.

Figure 7-2 shows the revenue and cost metric for the drifting mill load cell.

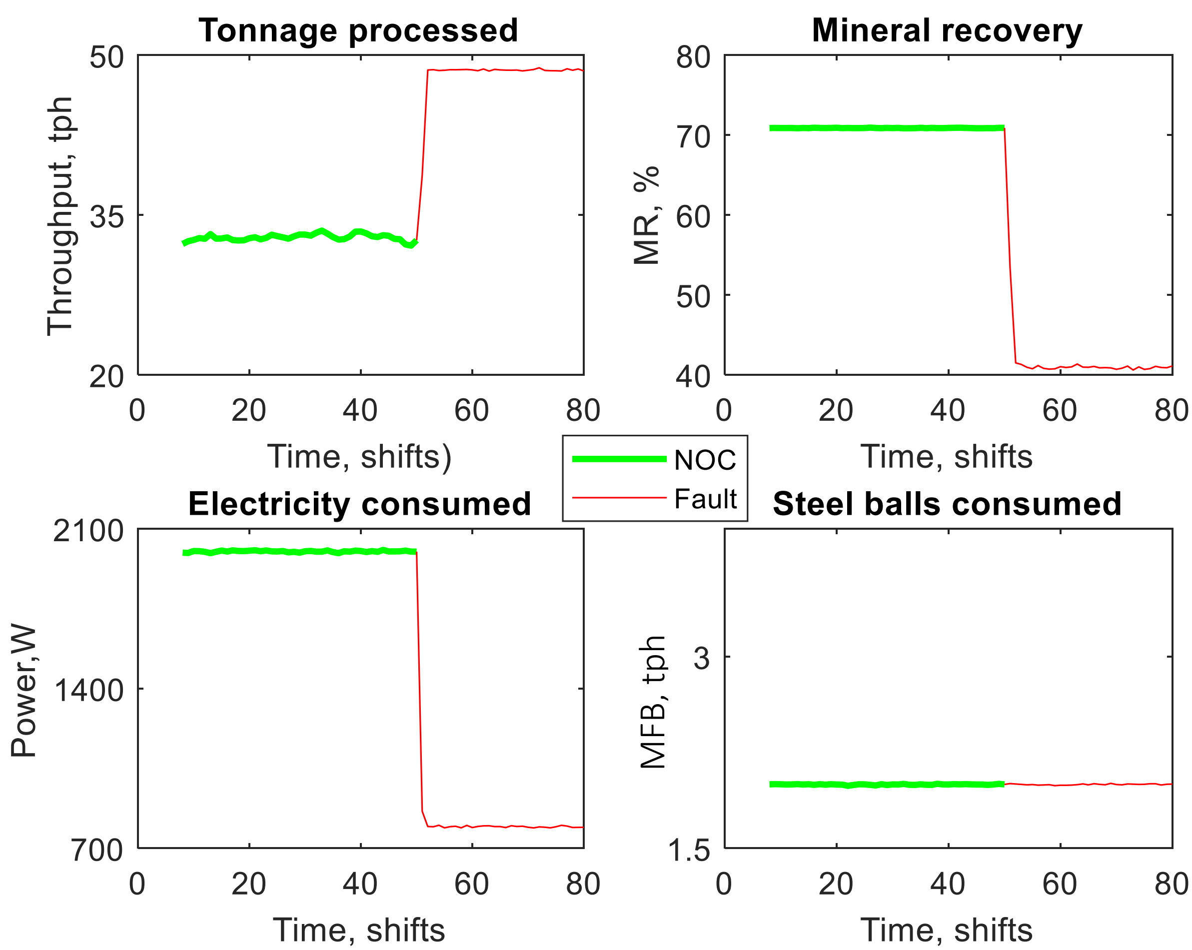


Figure 7-2: Revenue and cost metrics for the drifting mill load cell

The mill throughput increased by about 33% due to an increase in mill feed solids. A 43% reduction in the mineral recovery was observed, indicating a trade-off between mill throughput and mineral recovery. Hence, the decrease in mineral recovery after fault inception corresponded to the coarse particle size achieved. A 31% decrease in the SAG mill electricity consumption was observed as a result of a coarser product. The steel ball consumption remained constant, with normal variation from random walks.

7.1.2 Poor steel ball quality fault

The CV-MV plots for poor steel ball quality are shown in Figure 7-3.

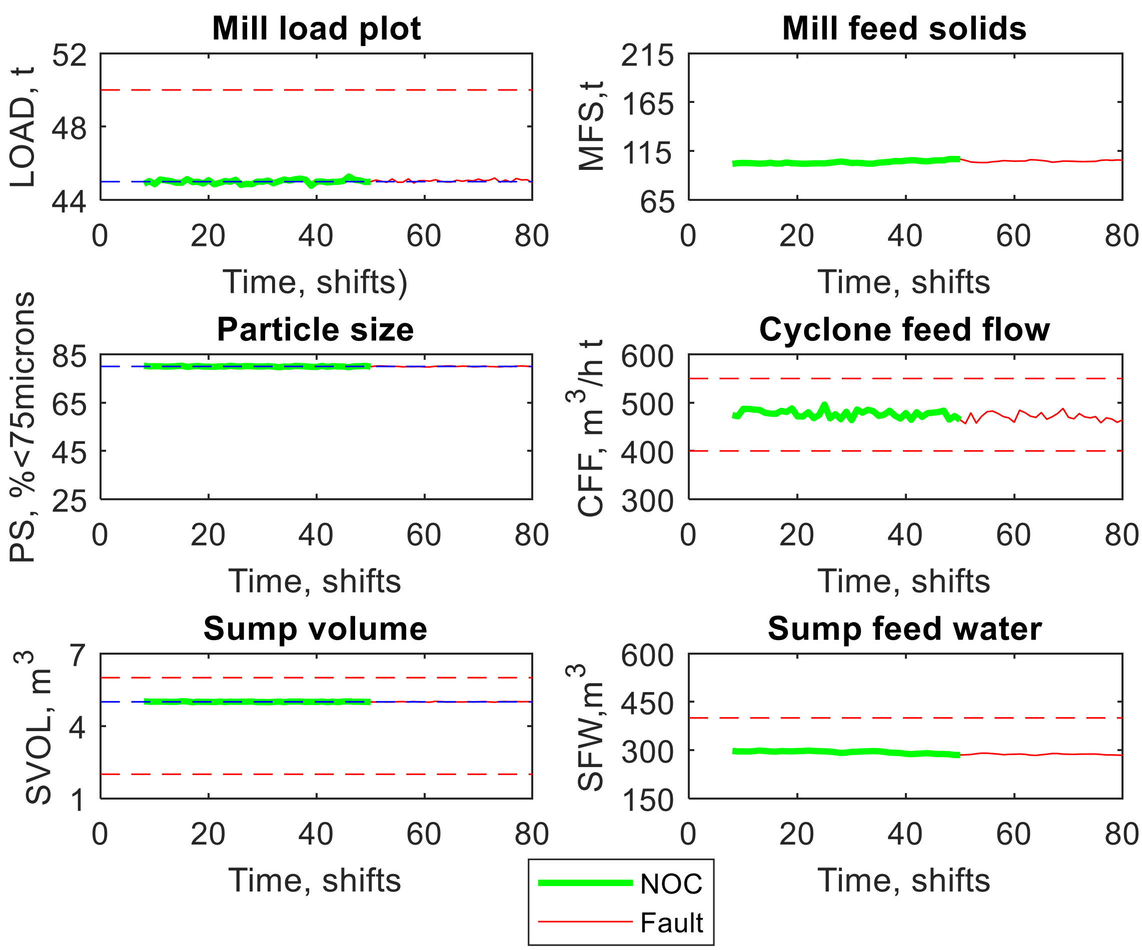


Figure 7-3: CV-MV plots for poor steel ball quality

All CVs and corresponding MVs showed normal variations introduced by random walks. The particle size was expected to coarsen due to poor grinding media impact and abrasive forces. As a result of increased steel ball addition, the mill feed solids were expected to be limited. Figure 7-3 shows that there was no fault propagation to the particle size as it remained around the target size. This showed that the only economic consequence was the cost arising from increased steel consumption. Figure 7-4 shows corresponding revenue and cost metrics.

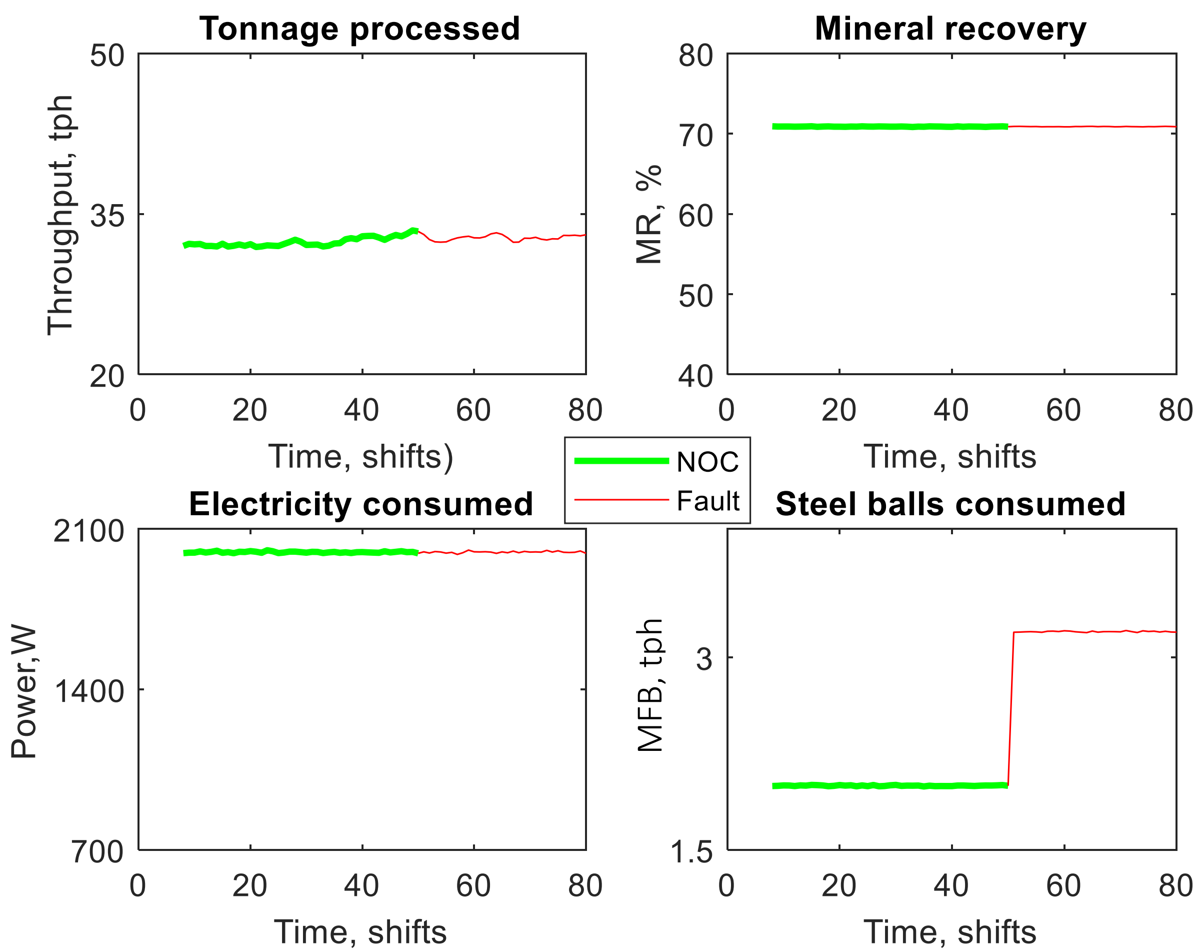


Figure 7-4: Revenue and cost metrics for poor steel ball quality

The revenue and cost metrics had normal variation except for steel ball charge rate which increased by a fault size of 60%.

7.1.3 Ore hardness increase

Figure 7-5 shows CV-MV plots for the increased ore hardness fault.

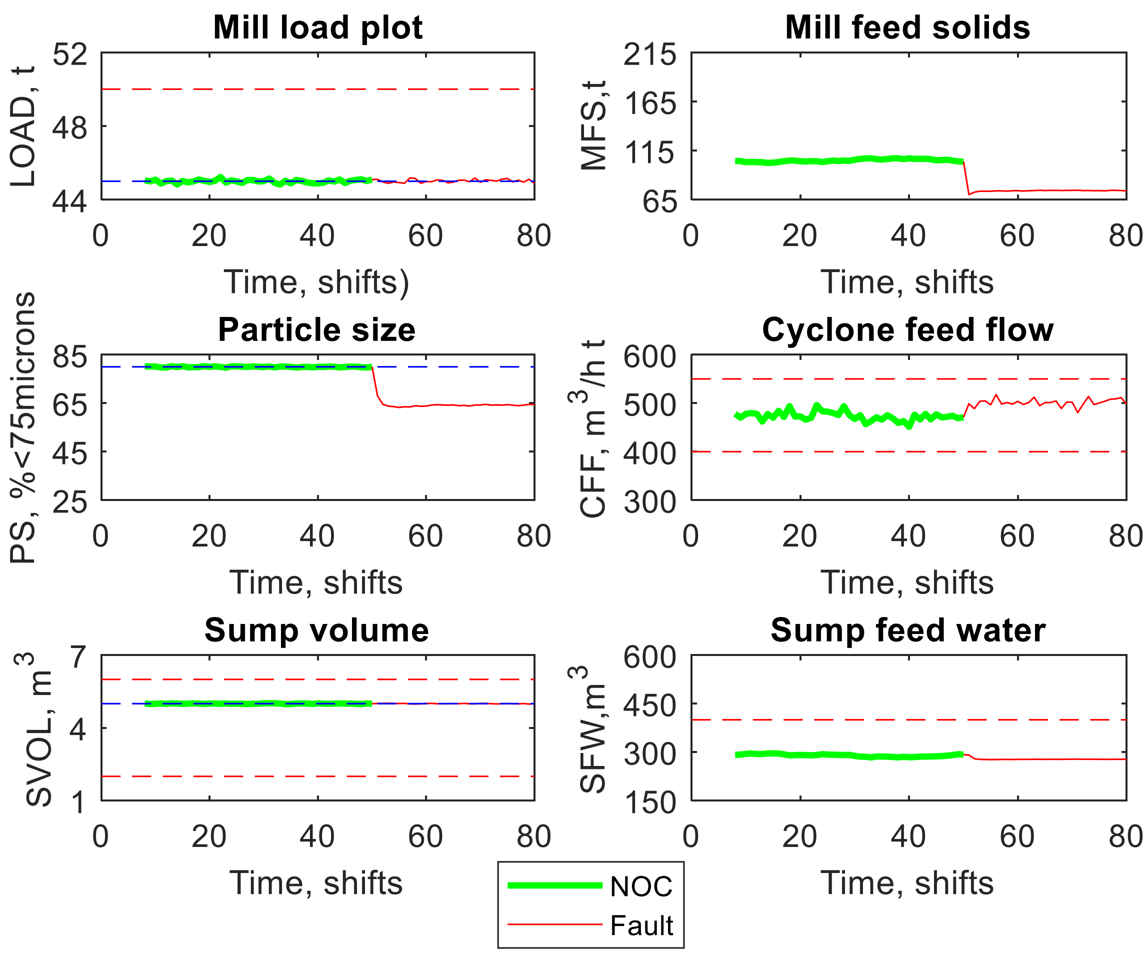


Figure 7-5: CV-MV plots for increased ore hardness

The mill load was well controlled around the set point as mill feed solids attenuated the effect of increased ore hardness. A 35% reduction in mill feed solids suggests a control effort to compensate for ore hardness changes, such that material discharged from the mill was recirculated for further grinding, in order to maintain mill load around the set point. Furthermore, a 4% increase in hydrocyclone flow feed supported the assertion on material recirculation for regrinding. Consequently, fresh ore feed was limited as shown by a decrease in mill feed solids. Although the PID controller showed some effort to minimize the effect of increased ore hardness, a coarser product with 65% passing 75µm was achieved. The sump volume was maintained around the set point due to a decrease in sump feed water caused by increased mill discharge rates into the sump. Hence, the PID controller showed effective stabilizing control of the mill load and sump volume.

Figure 7-6 shows the corresponding revenue and cost metrics.

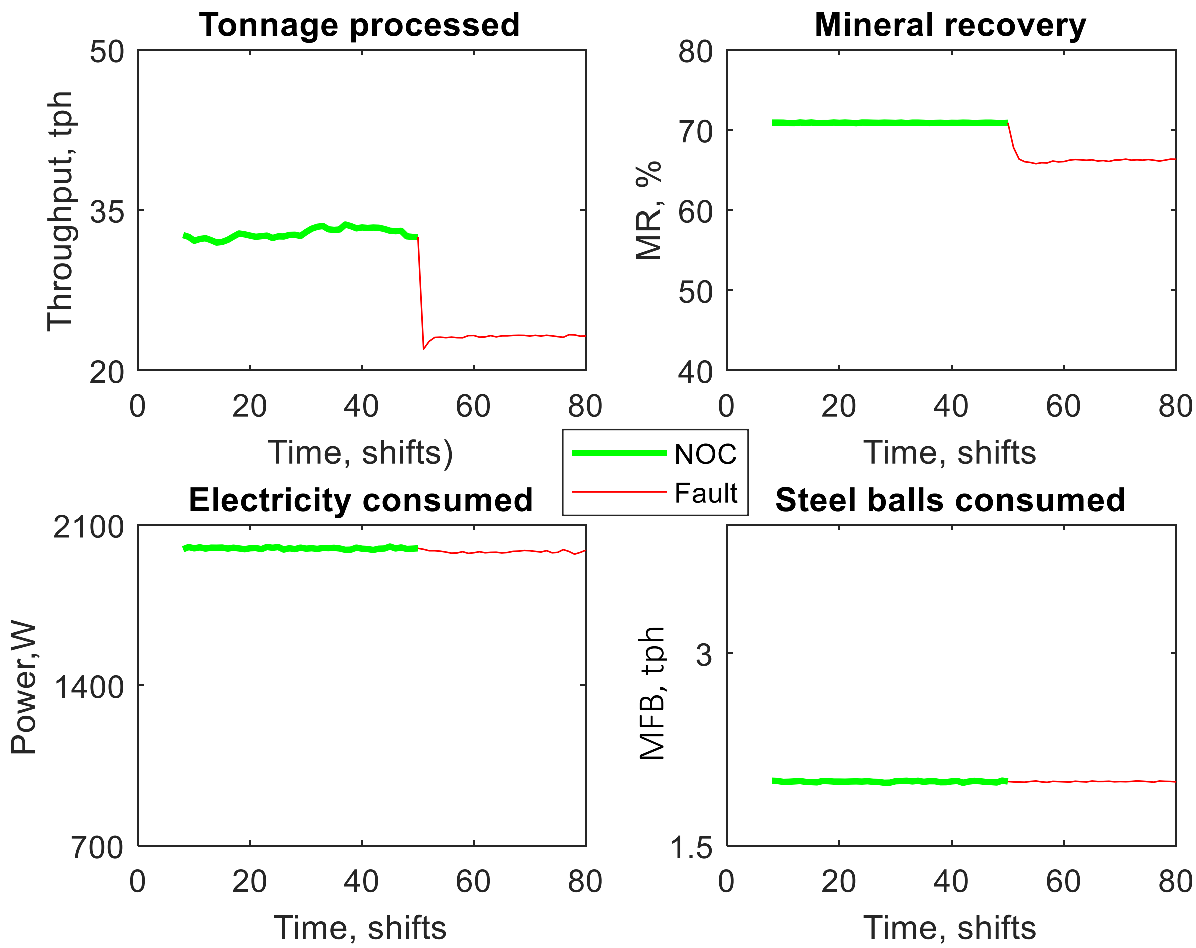


Figure 7-6: Revenue and cost metrics for increased ore hardness

The mill throughput decreased by 32% due to increased ore grinding resistance and hence, a longer ore retention time. This decrease was similar to that observed for the mill feed solids. The mineral recovery sharply decreased by 7% due to the low degree of liberation achieved. Although electricity consumption was expected to increase with abrasive ore feed, a 10% decrease was observed. As a possible inference, less power was required to regrind the recirculating material. The target particle size was not achieved despite increased grinding time.

7.1.4 Summary for simulated faults

Stabilizing the grinding mill circuit has been key to successful industrial circuit operation, hence the use of process control systems. As such, simulation experiment results showed economic consequences with changes in CVs, to support literature findings on the cost implication of process variability when CVs move away from a profitable operating mean. This was particularly observed for the particle size, which was directly related to mineral recovery. Furthermore, changes in process conditions (for the drifting load cell and increased ore hardness) resulted in variable flow throughout the circuit and delivery of material that is inconsistent with the required target particle size of 80% passing 75µm.

The SAG mill is operated with an objective to liberate mineral value for downstream recovery. By convention, mineral recovery is improved within an optimal particle size range. In all the simulation results, the correlation between the particle size and mineral recovery was evident. Furthermore, the trade-off relationship between the particle size and throughput was observed for poor steel ball quality and increased ore hardness faults.

Two of the faults (drifting load cell and poor quality steel ball) showed significant changes of 32% and 60% in the mill throughput and the steel ball charge rate, respectively. In addition, process control action to attenuate the impact of fault conditions introduced in the model either limited the throughput, or produced a coarse product. Either outcome affected revenue or cost elements, to emphasize the significance of these metrics in the EPI. Moreover, industrial operations employ tonnage maximisation and cost minimisation strategies. Therefore, the significance of these metrics justifies their inclusion when the economic performance of milling circuits is assessed.

The increased ore hardness fault showed a decrease in both the mill throughput and the particle size. This may have been as a result of the large fault size which limited the throughput and resulted in a coarser product size. Typically, increased ore abrasiveness results in higher electricity and steel ball demands in order to grind the ore to target particle size (King, 2001). However, the simulation results indicated decreased electricity consumption and did not reflect any significant changes in the steel ball consumption. The poor steel ball quality fault did not reflect any significant changes in the operating conditions. A decrease in the mill throughput was expected since more steel balls would have been charged into the mill to maintain ore-steel ball ratio. However, the particle size was then expected to coarsen since no changes were observed for the mill feed solids. Despite the identified anomalies, the results showed that fault detection was possible with an EPF model.

7.2 Significance tests

Appendix P and Appendix R list mineral recovery and mill throughput data respectively, for each of the 15 simulation experiments. Table 7-1 presents F-test and p-value results based on this data.

Table 7-1: F-test results

	Mineral recovery	**Mill throughput**
F_{crit} - critical, Where $df_1 = 2$, $df_2 = 12$	3.89	3.89
F_{ob} - observed,	71.99	25.44
Condition $F_{ob}>F_{crit}$ Reject null hypothesis of equal sample means	Reject null hypothesis	Reject null hypothesis
p-value	2.07E-07	4.83E-05
Condition p-value<0.05 Reject null hypothesis of equal sample means for the three faults	Reject null hypothesis	Reject null hypothesis

For both the mineral recovery and mill throughput, F-test and p-value results indicate at least one significant difference between sample means for the three faults. Hence, a Tukey-Kramer post-hoc analysis was conducted to identify the different means. The pairwise comparisons of p-values are shown for the mineral recovery and mill throughput in Table 7-2.

Table 7-2: Pairwise p-values

Pairs	**Mineral recovery**	**Mill throughput**
1,2	2.25E-07	0.001
1,3	3.99E-06	4.04E-05
2,3	0.06	0.10

Where *1,2,3* are the drifting load cell, poor steel ball quality and increased ore hardness faults

The results show p-values < 0.05 between the drifting load cell – poor steel ball quality *(1,2)* and the drifting load cell – increased ore hardness *(1,3)* faults, pointing to a significant difference between the drifting load cell fault and the other two faults. The box plots shown in Figure 7-7 and Figure 7-8 for mineral recovery and mill throughput respectively, validate this finding.

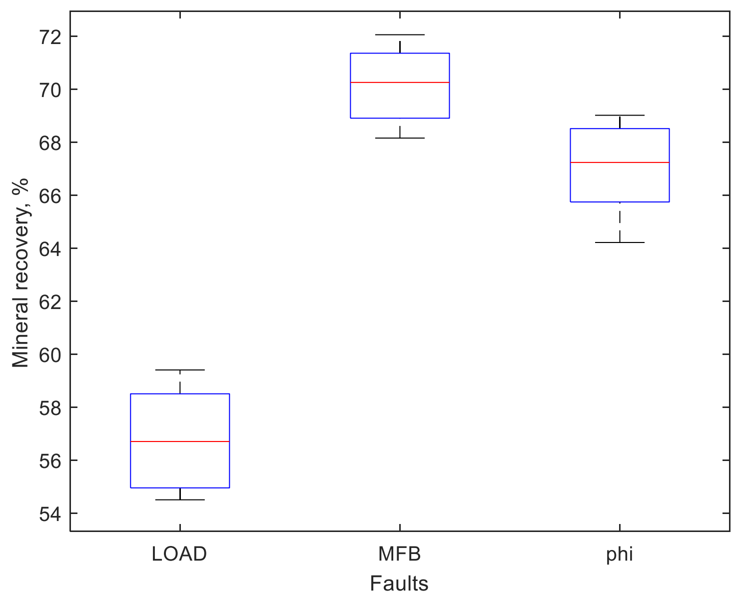


Figure 7-7: Mineral recovery box plot

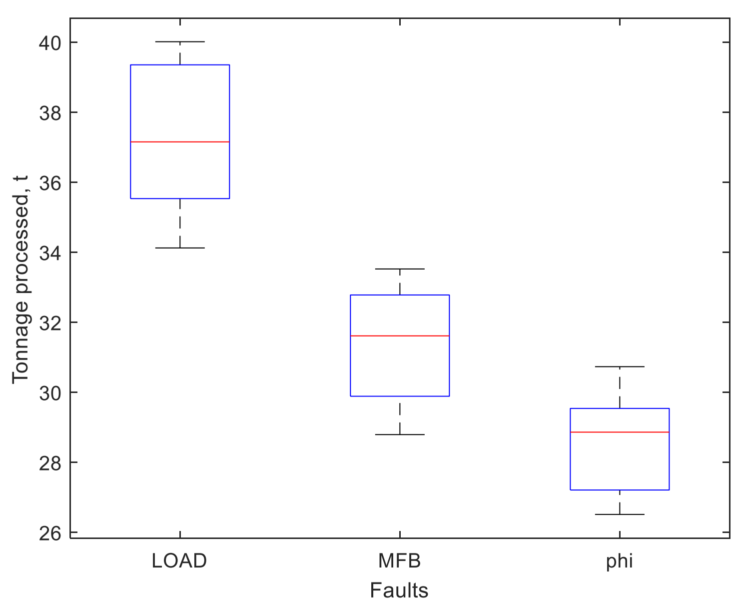


Figure 7-8: Mill throughput box plot

7.3 Economic performance indices for simulated faults

Sliding window normalized EPIs for all three simulated faults are shown in Figure 7-9.

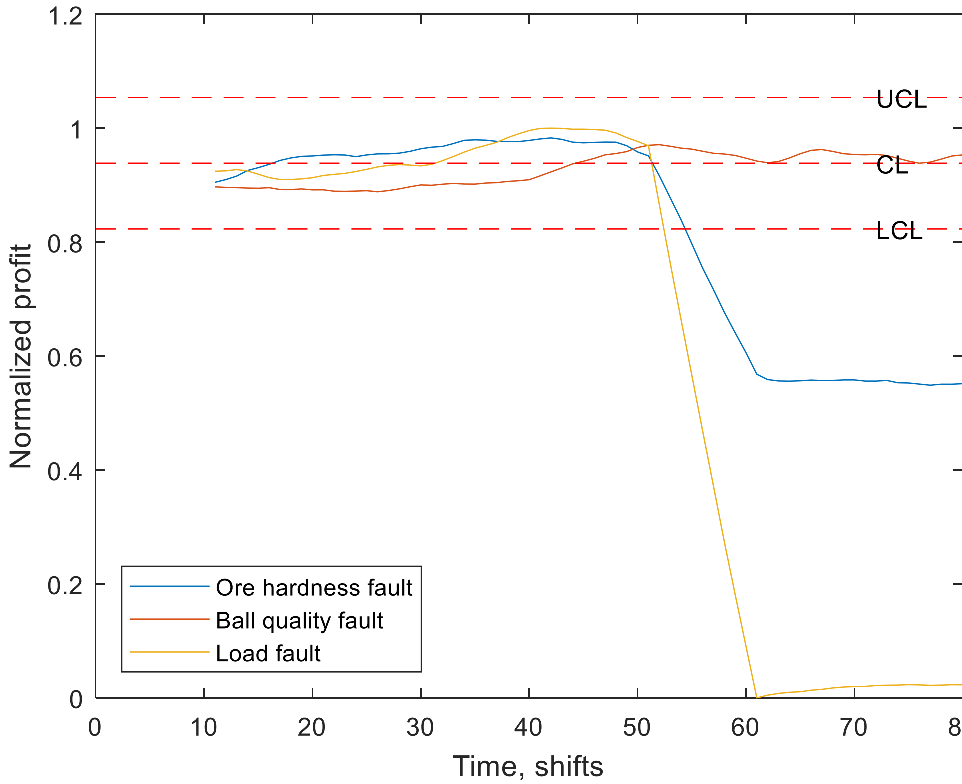


Figure 7-9: Sliding window economic performance indices

All three faults show different NOC economic performances due to process noise introduced through random walks. Minimal change is observed for the poor steel ball quality after fault inception at 50 shifts. Although there was a cost associated with extra ball charge, the sliding EPI shows little variability around the NOC (shown as CL) after fault inception. The EPI did not degrade and hence, this fault showed the least economic impact. The drifting load cell and increased ore hardness faults show significant deviation from normal operating economic performance after fault inception. In this assessment, the economic impact of the ore hardness fault was greater compared to that for a drifting load cell.

In Figure 7-9, process noise variability does not reflect significant changes in the EPI. However, there is a significant degradation in the EPI due to large disturbances introduced by two faults (drifting load cell and increased ore hardness). Hence, the EPI shows potential for fault (large disturbances) detection. Moreover, significance test results pointed to the difference between a drifting load cell and the other two faults. The results suggest opportunity to prioritise faults and make decisions about the corrective action to be taken, based on the severity of impact on economic performance. It is reasonable to allow a fault with very little impact on the EPI to persist. However, serious corrective action such as a shutdown for maintenance may be considered for faults with a large impact on the EPI. A similar concept is discussed in Olivier & Craig (2017).

The simulation results show that changes in economic performance were influenced to a greater extent by revenue metrics i.e., changes in the particle size and hence, mineral recovery as well as changes in the mill throughput. On this merit, the study of Wei & Craig (2009a) used mineral recovery to represent economic performance. However, there was at least one significant change in either cost element (electricity or steel ball consumption) for two of the simulated faults (drifting load cell and poor steel ball quality) presented in Figure 7-2.

Since grinding operations are energy intensive and require large amounts of grinding media, the EPI is more representative when the two cost elements are incorporated. The drifting load cell fault resulted in a 31% decrease in electricity consumption while poor steel ball quality also influenced steel ball consumption rates. Based on these findings, revenue metrics alone may be inadequate for industrial operations since cost minimisation strategies are employed in industrial operations. Therefore, electricity and steel ball consumption must be considered when deriving the economic performance of a milling circuit.

Chapter Summary

Chapter 7 investigated the merit of fault detection with the economic performance index, based on deviation from normal operating performance. To this end, three common faults in a milling circuit were simulated. A sliding window EPI was derived for each fault, using *a priori* particle size-mineral recovery EPF as well as key revenue and cost metrics. The simulation results showed scope for fault detection and prioritisation with the EPI. Two of the faults (drifting load cell and increased ore hardness) showed significant EPI degradation after fault inception. Moreover, a significant difference between the economic impact of the drifting load cell fault and the other two faults (poor steel ball quality and increased ore hardness) was observed, pointing to scope for fault prioritisation.

The next Chapter concludes this study with a summary of the findings and recommendations for future work.

CHAPTER 8: CONCLUSION AND RECOMMENDATIONS

Study background and objectives summary

Milling circuit operations are driven with a profit maximisation objective, and decisions for consistent profitability are enabled by effective process monitoring. Although it is beneficial to monitor all the variables in milling circuits, only a few are directly controlled for economic reasons. Therefore, this study aimed to assess the feasibility of monitoring milling circuits with economic performance functions (EPFs). These relate the behaviour of a controlled variable about a profitable set point, to money. To achieve the aim of the study, industrial and simulation cases were studied. The objectives of the industrial case study were:

1. To develop a reliable EPF with industrial primary mill and rougher flotation data;
2. To derive the circuit's benchmark economic performance;
3. To assess the feasibility of industrially implementing an online process monitoring tool for the circuit, using one key controlled variable; and
4. To assess the feasibility of incorporating additional key controlled variables in the process monitoring tool.

The proof of concept was tested in a simulation case study, where *a priori* EPF developed at laboratory scale was used to investigate fault detection with EPFs. Fault detection is a critical aspect of process monitoring that minimizes the occurrence of faults and their economic impact. Therefore, the following objectives were identified for the simulation case study:

1. To derive the economic performance of a SAG mill circuit subject to three common industrial faults; and
2. To assess the economic impact of the fault events and subsequently, determine fault detection feasibility with EPFs.

Industrial case study summary methodology and findings

Data for EPF and process monitoring tool development were judiciously identified based on in-depth literature survey, a site survey at the industrial operation and consultations with expert site personnel. Historical data for the years January 2012 till April 2016 were retrieved from the plants historian, control room log sheets, laboratory data archives and financial reports. The data were well documented, so an assessment of EPF development and economic performance evaluation for the primary mill and rougher flotation circuit was possible.

Three key controlled variables i.e. mass pull, particle size and mill load were selected based on the expert opinion of consulted site personnel. However, this selection can also be validated by several literature. Single predictor regression was performed with particle size (the key controlled variable) and multi-predictor regression was also performed to incorporate two additional controlled variables (mass pull and mill load). For each of these regressions, financial elements analysis (FEA) and process variable analysis (PVA) were investigated using base case data, as well as sliding window searches for EPFs throughout all the historical data. Significant revenue (throughput and mineral recovery) and cost elements (electricity, reagents and steel balls) were used to derive the profit realised from operating the industrial primary mill and rougher flotation circuit. Consequently, this profit was related to CV behaviour in the FEA approach. On the other hand, the PVA approach related CV behaviour to mineral recovery.

Results for the industrial case study showed that it was difficult to develop a reliable EPF using either FEA or PVA approaches. This concurred with the finding in Wei & Craig (2009c) and Bauer & Craig (2008) on the difficulty to develop EPFs with industrial data. EPF model adjusted R-squared values fell below a selected significance threshold of 0.6, to indicate poor model fit. Furthermore, model predictions were not in agreement with plant test data. Consequently, it was not possible to implement the process monitoring tool at the industrial operation. In addition, incorporating two more economically significant CVs into the EPF model did not improve the results.

Two points of interest emerged from the results in the study. Firstly, it was not possible to identify the conventionally quadratic relationship between particle size and mineral recovery throughout all the data. Although a wide range for particle size data may have been good for EPF model development, particle size measurements were rather too erratic. Giddy (1988) refer to erratic particle size as a typical occurrence since primary mills are operated as tonnage mills controlled with an objective to maximise throughput, rather than to achieve the target particle size. The second interesting finding was that despite *a priori* knowledge of the strong interactions between milling circuit controlled variables (Hodouin, 2011; Wills & Napier-Munn, 2006), variables for the primary mill and rougher flotation circuit were characterized by weak correlation coefficients of less than 0.2.

The development of EPF models is premised on having significantly variable process data. Model data variability was possibly insufficient for EPF development, due to robust model predictive controller action. In addition, limitations in data cleaning techniques, data quality and proposed model structure also accounted for the poor EPF models.

A major shortcoming for reliable data analysis and subsequently, EPF model development was resolution mismatch between offline and online data was. At the industrial operation, shift composite samples are analysed offline for particle size and mineral recovery measurements. Hence, the true process dynamics are insufficiently captured by these 'averaged' measurements. Similarly, shift averages for 30 minute time-stamped online data were determined in order to match the offline shift data. Doing this also smoothed out data dynamics and it was therefore difficult to identify unique process states due to loss of variability. The data cleaning techniques applied for faulty data resulted in loss of information. Faulty data and corresponding measurements in the other key variables were deleted, in order to preserve functional relationships between variables. This reordered data sequences, disturbed the time series effect and important in-between events were missed.

Both offline and online data had some anomalous and out of range entries, which had to be filtered out. Factors related to sensor accuracy and calibration frequency, as well as differing sensor qualities across the measured variables for the years under consideration influenced data quality. Although no correlations were identified between the data, the proposed model structure may have been too simple for milling circuit variables, which typically strongly interact.

While it was difficult to obtain a reliable EPF model for this case study, it was possible to derive the primary mill circuit's economic performance in terms of financial profit. Methodology steps to apply performance models to process monitoring and test process monitoring tool validity were discussed in this study, although it had not been possible to develop and implement the process monitoring tool.

Simulation case study findings

Simulation results showed a dynamic EPI in response to changes in operating conditions *vis-à-vis* process noise and fault conditions. After fault inception, two faults (drifting mill load cell and increased ore hardness) showed marginal EPI degradation. Hence, fault detection was possible with the investigated EPF. One-way ANOVA significance tests pointed to at least one difference between EPI values for drifting load cell and the other two faults. This finding suggests opportunity for fault prioritisation with EPFs, such that decisions on corrective action can be reached based on the severity of impact on economic performance. A similar concept is discussed in Olivier & Craig (2017). However, this study associated EPI values with specific fault types that were simulated in the SAG mill circuit, and did not fully explore this finding. Fault sizes can vary, to result in completely different EPI values, which may even overlap with a different type of fault in industrial operations.

Although necessary, simplifying assumptions pose certain limitations and economic consequences that are difficult to account for adequately. To give a few examples, an unstable SAG mill circuit minimizes the efficiency of downstream processes, to result in loss of performance. In addition, unstable hydrocyclone feed flow rates (shown for the drifting load cell and increased ore hardness) induce variability in flotation feed, to result in mineral losses. Furthermore, a coarse flotation feed may require more reagents, especially the collector (Bahena *et.al.* 2006). Due to insufficient model information, other economically significant consequences such as increased liner wear from operating the mill at a high load were not taken into consideration, in order to simplify the economic performance assessment.

Recommendations for future work

Some areas of interest in this study were identified for future work. In many industrial operations, focus is mostly directed to meet and even better, surpass production targets to maximise revenue. In comparison, less attention is paid to manage cost variation within production operations. Therefore, a recommendation to use financial elements to monitor the primary mill circuit's economic performance online is proposed.

Following this recommendation, process decisions that maximize profit may be reached through manipulating revenue and cost metrics associated with the process. This provides opportunity to interrogate any performance deviations, and to simultaneously optimise all the key economically significant metrics for the primary mill circuit. Consequently, process decisions can be reached earlier on in the process, rather than retrospectively after accounting reports have been generated.

Despite the challenges faced in this study, the few successful EPA studies (e.g., Bauer *et al.*, 2007; Steyn & Sandrock, 2013; Wei & Craig, 2009a) demonstrated for controller performance , process monitoring with EPFs seems to be a promising avenue which requires further investigation. Since reliable EPF development was the main limitation in this study, a comparative assessment in a different operation which addresses the shortcomings identified in this study is recommended. Moreover, the shortcomings identified in some of the simplifying assumptions will need to be addressed in future work.

REFERENCES

Aldrich, C. 2013. Consumption of steel grinding media in mills – A review. *Minerals Engineering*. 49:77–91.

Almond, D.G. & Valderrama, W. 2004. Performance enhancement tools for grinding mills. *International Platinum Conference "Platinum Adding Value"*. 103–110.

Almond, D., Becerra, K. & Campain, D. 2012. The Minerals Plant of the Future – Leveraging Automation and Using Intelligent Collaborative Environment. *The Southern African Institute of Mining and Metallurgy Platinum 2012*.

Alt, F.B. & Smith, N.D. 1998. *Multivariate process control*. New York: Elsevier Science Publisher.

Aly, A.A., Mahmoud, M.A. & Woodall, W.H. 2015. A Comparison of the Performance of Phase II Simple Linear Profile Control Charts when Parameters are Estimated. *Communications in Statistics—Simulation and Computation*.

Arteaga, F. & Ferrer, A. 2002. Dealing with missing data in MSPC: Several methods, different interpretations, some examples. *Journal of Chemometrics*. (16):408–418.

Arzen, K. 1991. "Knowledge based applications in the processs industry: Current state and future directions". In Bergen, Norway *IFAC Proceedings on Computer software structures integrating AI/KBS Systems in Process Control*.

Babcock, B., Datar, M. & Motwani, R. 2002. Sampling From a Moving Window Over Streaming Data. *Proceedings of 13th Annual ACMSIAM Symposium on Discrete Algorithms*. 102(2001–33):633–634. [Online], Available: http://ilpubs.stanford.edu:8090/503/1/2001-33.pdf.

Ballantyne, G. & Powell, M. 2014. Benchmarking comminution energy consumption for the processing of copper and gold ores. *Minerals Engineering*. 65:109–114.

Barton, R. 2013. Designing simulation experiments. *Proceedings of the 2013 Winter Simulation Conference*. 342–353.

Bartsch, E., Comeau, G., Hardie, C. 2008. Evolution of SAG Mill Process Control at the Xstrata Nickel Raglan Operation. In *40th Annual Meeting of the Canadian Mineral Processors*. 445–464.

Bauer, M. & Craig, I.K. 2008. Economic assessment of advanced process control - A survey and framework. *Journal of Process Control*. 18(1):2–18.

Bauer, M., Craig, I.K., Tolsma, E. & de Beer, H. 2007. A Profit Index for Assessing the Benefits of Process Control. *Industrial & Engineering Chemistry Research*. 46(17):5614–5623.

Baxter, P., & Jack, S. 2008. Qualitative Case Study Methodology: Study Design and Implementation for Novice Researchers. *The Qualitative Report*. 13(4):544–556.

Beigler, L. 2010. *Nonlinear Programming: Concepts, Algorithms, and Applications to Chemical Processes*. New York: SIAM-Society for Industrial and Applied Mathematics.

Ben-Gal, I. 2005. *Outlier detection*. O. Maimon & L. Rockach (eds.). Kluwer Academic Publishers.

Benneyan J.C. 2001. Design, Use and Performance of Statistical Control Charts for Clinical Process Improvement. *International Journal for Quality Health*. 69–73.

Besterfield, D. 2001. Quality control. *Upper Saddle River, NJ:*. Prentice Hall.

Bezergianni, S. & Georgakis, C. 2003. Evaluation of controller performance?use of models derived by subspace identification. *International Journal of Adaptive Control and Signal Processing*. 17(7–9):527–552.

Boque, R., Smilde, A.K. 1999. Monitoring and diagnosing batch processes with multiway covariates regression models. *American Institute of Chemical Engineers*. 30:1429–1432.

Bouffard, S.C. 2015. Benefits of process control systems in mineral processing grinding circuits. *Minerals Engineering*. 79:139–142.

Box, G., and Luceno, A. 1997. Discrete proportional integral adjustment and statistical process control. *Journal of Quality Technology*. 29(3):248–259.

Braverman, V., Ostrovsky, R. & Zaniolo, C. 2009. Optimal sampling from sliding windows. In *ACM PODS, Providence*. 1–13.

Brisk, M.L. 2004. Process Control : Potential Benefits and Wasted Opportunities. *5th Asian Control Conference Process*. 10–16.

Bryman, A. & Bell, E. 2007. The nature of qualitative research. In: Business Research Methods. *New York. Oxford University Press.*

Buchanan, D.. & Bessant, J. 1985. Failure, uncertainty and control: the role of operators in computer integrated production systems. *Journal of Management Studies*. 22(3):292–308.

Castle, J. F. & Imre, U. 1984. Exploitation staretgy for complex Cu-Pb-Zn orebodies. *Mineral Engineering*. 12(2):473–477.

Cha, Y. & Agrawal, A. 2014. Robustness studies of sensor faults and noises for semi-active control strategies using large-scale magnetorheological dampers. *Journal of Vibration and Control*. 1–16.

Chandola. 2009. Anomaly Detection for Symbolic Sequences and Time Series Data. *University of Minnesota*. Doctor Of Philosophy.

Clermont, B. & De Haas, B. 2010. Optimization of mill performance by using online ball and pulp measurements. *Journal of the Southern African Institute of Mining and Metallurgy*. 110(3):133–140.

Coetzee, L.C., Craig, I.K. & Kerrigan, E.C. 2008. Nonlinear model predictive control of a run-of-mine ore milling circuit. In *Proceedings of the 17th IFAC World Congress. Elsevier, Korea*. 10620–10625.

Coetzer, L.P. & Khumalo, T. 2006. The use of performance monitoring techniques in detecting process shifts and potential root causes in a variable speed grinding application. *The Southern African Institute of Mining and Metallurgy*. 2:137–142.

Contreras-Dordelly, J. & Marlin, T.E. 2000. Control design for increased profit. *Computers & Chemical Engineering*. 24:267–272.

Contreras-Dordelly J.L, M.T. 2000. Control design for increased profit. *Computers and Chemical Engineering*. 24:267–272.

Craig, I.K. & Henning, R.G.D. 2000. Evaluation of advanced industrial control projects: a framework for determining economic benefits. *Control Engineering Practice*. 8(7):769–780.

Craig, I.K. & Koch, I. 2003. Experimental design for the economic performance evaluation of industrial controllers. *Control Engineering Practice*. 11(1):57–66.

Craig, I.K. & Macleod, I. 1996. Robust controller design and implementation for a run-of-mine ore milling circuit. *Control Engineering Practice*. 4(1):1–12.

Creswell, J. 2003. *Research design: Qualitative, quantitative and mixed methods approaches*. 2nd ed. CA: Thousand Oaks.

Cutler, C.R. & Perry, R.T. 1983. Real time optimization with multivariable control is required to maximize profits. *Computers and Chemical Engineering*. 7(5):663–667.

Denzin, N. 1998. *The art and politics of interpretation*. CA: Thousand Oaks.

Desborough, L. & Miller, R. 2002. Increasing Customer Value of Industrial Control Performance Monitoring — Honeywell ' s Experience. *Sixth International Conference on Chemical Process Control, AIChE Symposium Series Number 326*. 98(Figure 1):169–189.

Dey, R., Pal, A., Biswas,A., Das, A. 2014. Creeping and Drifting Correction of Sensor Using Adaptive Method. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*. 3(1):6670–6672.

Duncan, A. 1986. *Quality control and industrial statistics*. Vol. 5th Editio. Chicago: Irwin.

Dvorak, D. & Kuipers, B. 1991. Process monitoring and diagnosis: a model-based approach. *IEEE Expert*. 6(3):67–74.

Edwards, R. & Vien, A. 1999. Application of a model-based size recovery methodology. *Control and Optimisation in Minerals, Metals and Materials Processing*. 147–160.

Edwards, R., Vien, A. & Perry, R. 2002. Strategies for the instrumentation and control of grinding circuits. *Society for Mining Metallurgy and Exploration*. 2130–2151.

Egbe, E.A.P. & Abubakre, O.K. 2013. Determination of the Bond ' S Work Index of Baban Tsauni (Nigeria) Lead-Gold Ore. *European Scientific Journal*. 9(12):78–86.

El-Farra, N. & Giridhar, A. 2008. Detection and management of actuator faults in controlled particulate processes using population balance models. *Chemical Engineering Science*. 63(5):1185 – 1204.

Ellis, M., Duranda, H., Panagiotis, D. & Christofides, B. 2014. A tutorial review of economic model predictive control methods. *Journal of Process Control*. 24:1156–1178.

Eriksson, P.-G. & Isaksson, A.J. 1994. Some aspects of control loop performance monitoring. *Control Applications, 1994., Proceedings of the Third IEEE Conference on*. (3):1029–1034 vol.2.

Fan, J. & Huang, L. 2001. Goodness-of-Fit Test for Parametric Regression Models. *Journal of American Statistical Association*. 96:640–652.

Filzmoser, P., Maronna, R. & Werner, M. 2007. Outlier Identification in High Dimensions. *Elsevier Science*. 5(1):23–27.

Fiske, T. 2006. Advanced process control for competitive advantage. *Hydrocarbon Processing*. 85(2):15–16.

Frankfort-Nachmias, C. & Nachmias, D. 1992. Research Methods in the Social Sciences*, Melbourne*. 4th edition.

Fry, H., Ketteridge, S. & Marshall, S. 1999. *A Handbook for Teaching and Learning in Higher Education*. Glasgow: Kogan Page.

Gertler J. 1998. *Fault detection and diagnosis in engineering systems*. New York: Marcel Dekker.

Ghasemi, B. & Zahediasl, C. 2012. Normality Tests for Statistical Analysis: A Guide for Non-Statisticians. *Journal of Applied Statistics*. 10(2):486–489.

Ghorbani, B. 2004. Initial transient phase of steady state simulation: Methods of its length detection and their evaluation.

Giddy, M. 1988. Identification of an industrial scale semi-autogenous grinding circuit for control purposes. University of the Witswatersand.

Griesel, H. 2008. Optimizing project value by defining and modelling key drivers in the concept phase. *Platinum in Translation*. 349–354.

Gulsecen, S. & Kubat, A. 2006. Teaching ICT to teacher candidates using PBL: A qualitative and quantitative evaluation. *Educational Technology & Society*. 9(2):96–106.

Gupta, A., Mathur, T., Stadler, K. & Gallestey, E. 2013. A pragmatic approach for performance assessment of advanced process control. *IEEE International Conference on Control Applications (CCA)*. 754–759.

Hachicha, W., Moussa, I., Kolsi, R. 2012. Integration of Statistical and Engineering Process Control in a Batch Processes Monitoring: Case of Alkyd Polymerization Reactor. *International Journal of Control and Automation*. 5:212–216.

Hamilton, C. 2015. Applied Multiple Regression and Correlation Analysis. *Journal of Applied Statistics*.

Hangos, K.M. & Tuza, Z. 2001. Optimal control structure selection for process systems. *Computers & Chemical Engineering*. 25(11–12):1521–1536.

He, K. & Meeden, G. (in press). Selecting the number of bins in a histogram : A decision theoretic approach. *Journal of Statistical Planning and Inference*. 61:49 59.

Heale, R. & Twycross, A. 2015. Validity and reliability in quantitative studies. *Evidence Based Nursing*. 18(3):15–18.

Herbst, J.A. & Lo, Y.C. 1996. Financial implications of comminution system optimization. *International Journal of Mineral Processing*. 44–45(SPEC. ISS.):209–221.

Herbst, J.A., Alba, F.J., Pate, W.T. & Oblad, A.E. 1988. Optimal control of comminution operations. *International Journal of Mineral Processing*.

Herman, A., Gottfredson, R. & Joo, H. 2013. Best-Practice Recommendations for Defining, Identifying, and Handling Outliers. *Organizational Research Methods*. 16(2):270–301.

Himmelblau. 1978. Fault detection and diagnosis in chemical and petrochemical processes. *Elsevier: Amsterdam*.

Hodouin, D. 2011. Methods for automatic control, observation, and optimization in mineral processing plants. *Journal of Process Control*. 21(2):211–225.

Hodouin, D., Jämsä-Jounela, S.L., Carvalho, M.. & Bergh, L. 2001. State of the art and challenges in mineral processing control. *Control Engineering Practice*. 9(9):995–1005.

Hoepfl, M.. 1997. Choosing qualitative research: A primer for technology education researchers. *Journal of Technology Education*. 1(9):11–14.

Hoo, K.A., Piovoso, M.J., Schnelle, P.D. & Rowan, D. A. 2003. Process and controller performance monitoring: overview with industrial applications. *International Journal of Adaptive Control and Signal Processing*. 17(7–9):635–662.

Horch, A. & Isaksson, A.J. 1999. A modified index for control performance assessment. *Journal of Process Control*. 9(June):475–483.

Huang, B., Shah, S.L. & Kwok, E.K. 1997. Good, bad or optimal? Performance assessment of multivariable processes. *Automatica*. 33(6):1175–1183.

Hugo, A. 2001. Process controller performance assessment. *Hydrocarbon Processing*. 80(4):85–90.

Hunt, J., Kojovic, T. & Berry, R. 2013. Estimating comminution indices from ore mineralogy, chemistry and drill core logging. *Proceedings of the Second AusIMM Geometallurgy Conference*. 173–176.

Ibrahim, K.A. 1996. Active statistical process control PhD Chemical and Process Engineering. University of Newcastle.

Irannajad, M., Farzanegan, A. & Razavian, S.M. 2006. Spreadsheet-based simulation of closed ball milling circuits. *Minerals Engineering*.

Isermann, R. & Balle, P. 1997. Trends in the application of model based fault detection and diagnosis of technical processes. *Control engineering practice*. 5(5):709–719.

Jakhu, M.. 1998. Process Control in Flotation Plants. *IIME*. 79–102.

James R. B, Carroll, C. & Young, G. 2007. Colorado Mineral and Energy Industry Activities.

Jämsä-Jounela, S.L., Poikonen, R., Vatanski, N. & Rantala, A. 2003. Evaluation of control performance: Methods, monitoring tool and applications in a flotation plant. *Minerals Engineering*. 16(11):1069–1074.

Jankovic, A. 2003. Variables affecting the fine grinding of minerals using stirred mills. *Minerals Engineering*.

Jankowski, T., Davis, G., Holmes, J. & Kemper, G. 2011. Increasing data historian efficiency. *IEEE Cement Industry Technical Conference (Paper)*.

Jearkpaporn, D., Montgomery, D.C., Runger, G.C. & Borror, C.M. 2005. Model-based process monitoring using robust generalized linear models. *International Journal of Production Research*. 43(7):1337–1354.

Jelali, M. 2006. An overview of control performance assessment technology and industrial applications. *Control Engineering Practice*. 14(5):441–466.

Kaka, A.P. 1999. The development of a benchmark model that uses historical data for monitoring the progress of current construction projects. *Engineering, Construction and Architectural Management*. 6(3):256–266.

Kang, H. 2013. The prevention and handling of the missing data. *Korean Journal of Anesthesiol*. 64(5):402–406.

Kano, M. & Nakagawa, Y. 2008. Data-Based Process Monitoring , Process Control , and Quality Improvement : Recent Developments and Applications in Steel. *Computers and Chemical Engineering*. 32(1–2):12–34.

Kawatra, S. K., Eisele, T. C.,Weldum, T., Larsen, D., Mariani, R., P.J. 2005. Optimization of Comminution Circuit Throughput and Product Size Distribution by Simulation and Control.

Kazemzadeh, R.B., Noorossana, R. & Amiri, A. 2009. Monitoring polynomial profiles in quality control applications. *The International Journal of Advanced Manufacturing Technology*. 42(7–8):703–712.

Keet, K. & Du Plessis, F. 2010. Flotation process optimization through frequent in-line grade measurement as an alternative to sampling surveys that deliver outdated results. In *The 4th International Platinum Conference, Platinum in transition "Boom or Bust", The Southern African Institute of Mining and Metallurgy*.

Khandalkar, B. 2015. Design and Analysis of Digital PID Controller A Review. 2(4):940–942.

King, P.. 2001. *Modelling and simulation of mineral processing systems*. First ed. Oxford: Butterworth-Heinemann.

Knorr, E.. & Ng, R.. 1997. A Unified Notion of Outliers: Properties and Computation. *American Association for Artificial Intelligence*. 219–222. [Online], Available:

http://www.aaai.org/Papers/KDD/1997/KDD97-044.pdf.

Knuth, K.. 2013. Optimal Data-Based Binning for Histograms. *ArXiv Physics e-prints*.

Kourti, T. & MacGregor, J.F. 1995. Process analysis, monitoring and diagnosis, using multivariate projection methods. *Chemometrics and intelligent laboratory systems*. 28:3–21.

Kresta, J. V., Marlin, T.E. & MacGregor, J.F. 1994. Development of Inferential Process Models Using PLS. *Computers Chenical Engineering*. 18(7):597–611.

Latour, P., Sharpe, J. & Delaney, M.1986. Estimating benefits from advanced control. *Instrument Society of America*. 25(4):13–21.

Laurila, H., Karesvuori, J. & Tiili, O. 2002. Strategies for Instrumentation and Control of Flotation Circuits. *Mineral Processing Plant Design, Practise and Control*. 1:2174–2195.

Law, A.M. & Kelton, W.D. 1991. Simulation, Modeling, and Analysis. *Journal of Modelling and Simulation*. 4:36–42.

Leal, F., da Silva CostaI, R.F., Barra MontevechiI, J., de Almeida, D. & Marins, F. 2011. A practical guide for operational validation of discrete simulation models. *Pesquisa Operacional*. 31(1):57–77.

Lees, F. 1973. Some data on the failure modes of instruments in the chemical plant environment. *Chemical Engineering*. 277:418–421.

Le Roux, J.D., Craig, I.K., Hulbert, D.G., Hinde, A.L. 2013. Analysis and validation of a run-of-mine ore grinding mill circuit model for process control. *Minerals Engineering*. 43-44:121–134.

Liu, Y. & Spencer, S. 2004. Dynamic simulation of grinding circuits. *Minerals Engineering*. 17(11–12):1189–1198.

Ma, Y., Gu, X. & Wang, Y. 2010. Histogram similarity measure using variable bin size distance. 114:981–989.

MacGregor, J. & Kourti, T. 1995. Statistical process control of multivariate processes. *Control Engineering Practice*. 95(451):403–414. [Online], Available:

http://www.jstor.org/stable/10.2307/2669484%5Cnhttp://www.sciencedirect.com/science/article/pii/0967066195000l4L.

Madakyaru, M., Harrou, F. & Sun, Y. 2017. Improved data-based fault detection strategy and application to distillation columns. *Process Safety and Environmental Protection*.

Mahmoud, M.A., Morgan, J.P. & Woodall, W.H. 2010. The monitoring of simple linear regression profiles with two observations per sample. *Journal of Applied statistics*. 37(8):1249–1263.

Marlin, T. E., Perkins, J. D., Barton, G. W., & Brisk, M.L. 1991. Benefits from process control: results of a joint industry-university study. *Journal of Process Control*. 1(57):83–86.

Marto, M.. & Wolfe, R.. 1962. Computer control for an ore beneficiation process. *Society of Mining Engineers of AIME*. 1–37.

Matthews, B. & Craig, I.K. 2013. Control Engineering Practice Demand side management of a run-of-mine ore milling circuit. *Control Engineering Practice*. 21(6):759–768.

McClure, K.S., Gopaluni, R.B., Chmelyk, T., Marshman, D. & Shah, S.L. 2014. Nonlinear process monitoring using supervised locally linear embedding projection. *Industrial and Engineering Chemistry Research*. 53(13).

McKinnon, M.. & Tipper, D. 1995. *A Comparison of Transient Period Detection Algorithms Applied to Markovian Queueing Systems*.

Mcnickle, D., Pawlikowski, K. & Stacey, C. n.d. Detection and Significance of the Initial Transient Period in Quantitative Steady-State Simulation. 1–12.

Mead, R. & Gilmour, S.G. 1988. Statistical Principles for the Design of Experiments. *Cambridge*.

Mitchell, J.D., Abhinava, K., Griffiths, K.., McGarvey, B., Seibert, K. & Sethuraman, S. 2008. Unit Operations Characterization Using Historical Manufacturing Performance. *Industrial & Engineering Chemistry Research*. 47(17):6612–6621.

Moema, J.S., Papo, M.J., Slabbert, G.A. & Zimba, J. 2009. Grinding media quality assurance for the comminution of gold ores. *The Southern African Institute of Mining and Metallurgy*. 27–34. [Online], Available: http://www.saimm.co.za/Conferences/WorldGold2009/027-034_MOEMA.pdf.

Montgomery, D.C. 1991. *Introduction to Statistical Quality Control*. 2nd ed. New York: John Wiley & Sons.

Moody, J. 2014. Process Monitoring with Restricted Boltzmann Machines. Stellenbosch University.

Morrell, S. & Valery, W. 2001. Influence of Feed Size on AG/SAG Mill Performance. *Mining and mineral process engineering*. 203–214.

Moys, M.H., Souza, D.E., Tshabalala, S. & Giddy, M. 1987. Use of an Energy Balance around the Mill Sump to Estimate Mill Discharge Density. *Application of Computers and Mathematics in the Mineral Industries*. 2:15–26.

Mular, A.L., Bond, T., Kingston, J.F. & Farnell, G.D. 1988. Instrumentation and control of a Continuous SAG mill circuit. *MINPRO International Journal of Mineral Processing*. 24(3):217–234.

Muske, K.R. & Finegan, C.S. 2001. Analysis of a class of statistical techniques for estimating the economic benefit from improved process control. 408–412.

Mwanga A., Lamberg P., Rozenkranz, J. 2015. Minerals Testing of Ore Comminution Behavior in the Geometallurgical Context—A Review. *Minerals Engineering*. 5:276–297.

Nel, E., Theron, J., Martin, C. & Raabe, H. 2004. *PGM ore processing at Impala's UG-2 Concentrator in Rustenburg, South Africa*.

Olivier, L.E. & Craig, I.K. 2017. Should I shut down my processing plant ? An analysis in the presence of faults ☆. *Journal of Process Control*. 56:35–47.

Oosthuizen, D.J., Craig, I.K. & Pistorius, P.C. 2004. Economic evaluation and design of an electric arc furnace controller based on economic objectives. *Control Engineering Practice*. 12(3):253–265.

Ostertagova, E. & Ostertag, O. 2013. Methodology and Application of One-way ANOVA,. *American Journal* *of Mechanical Engineering*. 1(7):256–261.

Patwardhan, R.S., Shah, S.L. & Q, K.Z. 2002. Assessing the Performance of Model Predictive Controllers. *The Canadian Jorunal of Chemical Engineering*.

Paulonis, M.A. & Cox, J.W. 2003. A practical approach for large-scale controller performance assessment, diagnosis, and improvement. *Journal of Process Control*. 13(2):155–168.

Performance, C.L., Von, I.A., Maschinenbau, A., Automatisierungstechnik, L., Jelali, M., Bouzid, S. & Lunze, J. 2010. Control System Performance Monitoring.

Pokrajcic, Z. Morrison, R. 2008. Evaluation by Simulation of Grinding Circuit Options to Improve Eco-Efficiency. *MEI Comminution'08 Conference*.

Pomerleau, A., Hodouin, D., Desbiens, A. & Gagnon, É. 2000. A survey of grinding circuit control methods: From decentralized PID controllers to multivariable predictive controllers. *Powder Technology*. 108(2–3):103–115.

Ponelis, S.. 2015. Using Interpretive Qualitative Case Studies for Exploratory Research in Doctoral Studies: A Case of Information Systems Research in Small and Medium Enterprises. *International Journal of Doctoral Studies*. 10:535–550.

Powell, M.S. & Morrison, R.D. 2007. The future of comminution modelling. *International Journal of Mineral Processing*. 84(1–4):228–239.

Powell, M.S., van der Westhuizen, A.P. & Mainza, A.N. 2009. Applying grindcurves to mill operation and optimisation. *Minerals Engineering*. 22(7–8):625–632.

Qin, J.S. 1998. Control performance monitoring — a review and assessment. *Computers & Chemical Engineering*. 23(2):173–186.

Qin, S.. & Yu, J. 2007. Recent developments in multivariable controller performance monitoring. *Journal of Process Control*. 17(3):221–227.

Radziszewski, P. 2013. Energy recovery potential in comminution processes. *Minerals Engineering*. 46–47:83–88.

Rahman, S.M.A.K Sathik,M.Mohamed Kannan, K.S. 2012. Multiple Linear Regression Models in Outlier Detection. *International Journal of Research in Computer Science*. 2(2):23–28.

Rajagopal, V. & Iwasaki, I. 1992. The properties and performance of cast iron. grinding media. *Mineral Processing Extractive Metallurgy*. 11:75–106.

Rajamani, R. & Herbst, J. 1991. Optimal control of a ball mill grinding circuit - Grinding circuit modeling and dynamic simulation. *Chemical Engineering Science*. 46(3):861–870.

Ramasamy, M., Narayanan, S.S. & Rao, C.D.P. 2005. Control of ball mill grinding circuit using model predictive control scheme. *Journal of Process Control*. 15(3):273–283.

Rato, T.J. & Reis, M.S. 2010. Statistical monitoring of control loops performance: An improved historical-data benchmark index. *Quality and Reliability Engineering International*. 26(8):831–844.

Reisinger, H. 1997. The impact of research designs on R2 in linear regression models: an exploratory meta-analysis. *Journal of Empirical Generalisations in Marketing Science*. 2.

Remes, A., Karesvuori, J., Pekkarinen, H. & Jämsä-Jounela, S.-L. 2006. Integrated approach to monitoring and control of mineral grinding processes. In *IFAC Proceedings*.

Riascos, L.A.M., Moscato, L.A. & Miyagi, P.E. 2004. Detection and treatment of faults in manufacturing systems based on Petri Nets. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*. 26(3).

Rice, R.C. & Cooper, D.J. 2005. Opening the Black Box : Demystifying Performance Assessment Techniques. 25–27.

Riebel, U. & Löffler, F. 1989. The Fundamentals of Particle Size Analysis by Means of Ultrasonic Spectrometry. *TOC*. 6(1–4):135–143.

Royston, P., Matthews, J.N. 1991. Estimation of reference ranges from normal samples. *Statistics in medicine*. 10(5):691–695.

Rule, C. & DeWaal, H. 2011. IsaMill design improvements and operational performance at Anglo Platinum. In Perth, Australia *MetPlant*.

Runge, K., McMaster, J., Ijsselstijn, M. & Andre, V. 2007. Establishing the Relationship between Grind Size and Flotation Recovery using Modelling Techniques.

Runge, K.C., Tabosa, E. & Jankovic, A. 2013. Particle Size Distribution Effects that Should be Considered when Performing Flotation Geometallurgical Testing. In *AUSIMM International Geometallurgy conference*. 335–344.

Rupare, W. F., Nyanga, L., Van Der Merwe, A. F., Matope, S., and Mhlanga, S. 2013. Design of an automated grinding media charging system for ball mills.

Sayadi, A.R., Khalesi, M.R. & Khosfarman, M. 2014. A parametric cost model for mineral grinding mills. *Minerals Engineering*. 55:96–102.

Schena, G., Villeneuve, J. & Noël, Y. 1996. A method for a financially efficient design of cell-based flotation circuits. *International Journal of Mineral Processing*. 46(1–2):1–20.

Schruben, L.W. 1982. Detecting Initialization Bias in Simulation Output. *Operations Research* . 30(3):569–590.

Schubert, J. H., Henning, R. G. D., Hulbert, D. G., & Craig, I.K. 1995. Flotation control—a multivariable stabilizer. *International Mineral Processing Congress*. XIX.

Serpas, M. 2012. Soft sensors for process monitoring of complex processes. A&M University.

Shah, S., Mitchell, W. & Shook, D. 2005. Challenges in the detection, diagnosis and visualisation of controller performance data. *IEE Computing & Control Engineering*. 31–34.

Shean, B.J. & Cilliers, J.J. 2011. A review of froth flotation control. *International Journal of Mineral Processing*. 100(3–4):57–71.

Siddiqui, Y.A., Saif, A.-W.A., Cheded, L., Elshafei, M. & Rahim, A. 2014. Integration of multivariate statistical process control and engineering process control: a novel framework. *The International Journal of Advanced Manufacturing Technology*. 78(1–4):259–268.

Silva, M. & Casali, A. 2015. Modelling SAG milling power and specific energy consumption including the feed percentage of intermediate size particles. *Minerals Engineering*. 70:156–161.

Simonsen, H. & Perry, J. 1999. Risk identification, assessment and management in the mining and metallurgical industries. *The Southern African Institute of Mining and Metallurgy*. 99(6):321–328. [Online], Available: http://www.saimm.co.za/Journal/v099n06p321.pdf.

Singh, N. 2013. Factors driving entrainment in flotation systems and implications for bank management. *Masters in Engineering*.

Skogestad, S. 2004. Control structure design for complete chemical plants. *Computers and Chemical Engineering*.

Sliškovic, D., Grbic, R. & Hocenski, Ž. 2011. Methods for Plant Data-Based Process Modeling in Soft-Sensor Development. *Automatika*. 52(4):306–318.

Smith, C.A. & Corripio, A.B. 1997. Principles and practice of automatic process control Solucionario Capitulo 13b. *Simulation*. 13–18.

Smith, G.C., Jordaan, L., Singh, A., Vandayar, V., Smith, V.C., Muller, B. & Hulbert, D. 2004. Innovative process control technology for milling and flotation circuit operations. *The Journal of The South African Institute of Mining and Metallurgy*. 353–366.

Smith, C.D., Hadler, K., Cilliers, J.J. 2010. Flotation bank air addition and distribution for optimal performance. *Minerals Engineering*. 23:1023–1029.

Sokolowski, J. & Banks, C.. 2010. *Modeling and simulation fundamentals Theoretical underpinnings and practical domains*. USA: John Wiley & Sons Inc.

Sosa-Blanco, C., Hodouin, D., Bazin, C., Lara-Valenzuela, C., Salazar, J. 2000. Economic optimisation of a flotation plant through grinding circuit tuning. *Minerals Engineering*. 13(10–11):999–1018.

Spero, C., Hargreaves D.J., Kirkcaidie R.K., F.H.J. 1991. Review of test methods for abrasive wear in ore grinding. *Mineral Engineering*. 146:389–408.

Stake, R.E. 1995. *The art of case study research*. CA: Sage: Thousand Oaks.

Steiner, S. H., & Mackay, J. 2000. Monitoring process with highly censored data. *Journal of Quality Technology*. 32:199–208.

Steyn, C.W. & Sandrock, C. 2013. Benefits of optimisation and model predictive control on a fully autogenous mill with variable speed. *Minerals Engineering*. 53:113–123.

Stover, F.S. & Brill, R. V. 1998. Statistical Quality Control Applied to Ion Chromatography Calibrations. *Journal of Chromatography*. 804:37–43.

Tatara, E. & Cinar, A. 2002. An Intelligent System for Multivariate Statistical Process Monitoring and Diagnosis. *ISA Transactions*. 41:255–270.

Taylor, S.L. 2010. Analyzing methods of mitigating initialization bias in transporttation simulation models

Tsay, R., Peña, D. & Pankratz, A.E. 2000. Outliers in multivariate time series. *Biometrika*. 87:789–804.

Valenta, M.M. & Mapheto, H. 2011. Application of fundamentals in optimizing platinum concentrator performance. *Journal of the Southern African Institute of Mining and Metallurgy*. 111(2):93–99.

Valery, W. & Jankovic, A. 2002. The Future of Comminution. In Bor Lake, Yugoslavia *Proceedings of 34th IOC on Mining and Metallurgy Conference,*.

Venkatasubramanian, R., Hayes, J. & Murray, B. 2003. Low-cost on-line fault detection using control flow assertions. In *9th IEEE On-Line Testing Symposium*. 137 – 143.

Venkatasubramanian, V., Rengaswamy, R. & Ka, S.N. 2003a. A review of process fault detection and diagnosis Part I: Qualitati v e models and search strategies. 27:313–326.

Venkatasubramanian, V., Rengaswamy, R. & Ka, S.N. 2003b. A review of process fault detection and diagnosis Part II : Qualitati v e models and search strategies. 27:313–326.

Veronesi, M. & Visioli, A. 2015. Deterministic Performance Assessment and Retuning of Industrial Controllers Based on Routine Operating Data: Applications. *Processes*. 3(1):113–137.

Votteler, R.G. & Brent, A.C. 2017. A mining perspective on the potential of renewable electricity sources for operations in South Africa : Part 2 – A multi-criteria decision assessment. *The South African Institute of Mining and Metallurg*. 117:299–312.

Wakefield, B.J. 2015. Process control and root-cause analysis of a run-of-mine ore mill circuit. Stellenbosch University.

Wang, K. & Tsung, F. 2005. Using Profile Monitoring Techniques for a Data-rich Environment with Huge Sample Size. *International Quality and reliability engineering*. 21:677–688.

Wei, D. 2010. Development Of Performance Functions For Economic Performance Assessment Of Process Control Systems. (February):1–6.

Wei, D. & Craig, I.K. 2009a. Economic performance assessment of two ROM ore milling circuit controllers. *Minerals Engineering*. 22(9–10):826–839.

Wei, D. & Craig, I.K. 2009b. Grinding mill circuits - A survey of control and economic concerns. *International Journal of Mineral Processing*. 90(1–4):56–66.

Weng, X. & Shen, J. 2008. Detecting outlier samples in multivariate time series dataset. *Knowledge-Based Systems*. 21(8):807–812.

White, D.C. 2003. The Economics of Advanced Automation. *Process Management*. 1–11.

Williams, R. & Dame, N. 2015. Interaction effects between continuous variables. 1–5.

Williams, M.C., Fuerstenau, D.W. & Meloy, T.P. 1986. Circuit analysis-General product equations for multifeed, multistage circuits containing variable selectivity functions. *International Journal of Mineral Processing*. 17(1–2):99–111.

Wills, B.A. & Napier-Munn, T. 2006. Mineral processing technology. 7th Edition:146–170.

Wood, M., Capon, N. & Kaye, M. 1998. User-friendly statistical concepts for process monitoring. *Journal of the Operational Research Society*. 49(9):976–985.

Woodall, W. 2016. Bridging the Gap between Theory and Practice in Basic Statistical Process Monitoring. In *4th STU Hunter Research Conference*.

Woodall, W.H., Spitzner, D.J., Montgomery, D.C. & Gupta, S. 2004. Using control charts to monitor process and product quality profiles. *Journal of Quality Technology*. 36(3):309–320.

Wu, X., Miao, R., Li, Z., Ren, J., Zhang, J. & Jiang, Z. 2015. Process monitoring research with various estimator-based MEWMA control charts. *International Journal of production research*. 53(14):4337–4350.

Xia, C., & Howell, J. 2003. Loop status monitoring and fault localization. *Journal of Process Control*. 13:679–691.

Xu, F., Huang, B. & Akande, S. 2007. Performance assessment of model predictive control for variability and constraint tuning. *Industrial & Engineering Chemistry Research*. 46:1208–1219.

Yang, R. & Hongjian, X. 2004. Process monitoring method in Largescale Production. *IEEE International Conference on Control Applications (CCA)*. 342–344.

Yen, C. & Shiau, J. 2010. A multivariate control chart for detecting increases in process dispersion. *Institute of Statistical Science*. 20(4):1683–1707.

Yin, K.K., Yang, H.C. & Cramer, F. 2002. On-line monitoring of papermaking processes. *Chemical Engineering Communications*. 189(9):1242–1261.

Yin, L., Zhang, H., Wang, A. & Wang, H. 2015. Disturbance Observer Based Optimal Setting Control for Complex Industrial Processes. (Cdc):1205–1209.

Yoo, C.K., Chooi, S.W., Lee, I. 2002. Dynamic monitoring method for multiscale fault detection and diagnosis in MSPC. *Ind. Eng. Chem. Res*. 41(17):4303–4317.

Yoon, K. & Hwang, C.. 1995. *Quantitative Applications in the Social Sciences,*. CA: Sage,: Thousand Oaks.

Yuan, Q. & Lennox, B. 2009. Control performance assessment for multivariable systems based on a modified relative variance technique. *Journal of Process Control*. 19(3):489–497.

Zaidah Z. 2007. Case study as a research method. *Jurnal Kemanusiaan*.

Zhang, J.. & Yan, Y. 2011. A wavelet-based approach to abrupt fault detection and diagnosis of sensors.

IEEE Transactions on Instrumentation and Measurement. 50(5):1389–1396.

Zhao, C., Zhao, Y., Su, H. & Huang, B. 2009. Economic performance assessment of advanced process control with LQG benchmarking. *Journal of Process Control*. 19(4):557–569.

Zhao, C., Xu, Q., Zhang, D. & An, A. 2011. Economic performance assessment of process control: A probability optimization approach. *2011 International Symposium on Advanced Control of Industrial Processes (ADCONIP)*. 585–590.

Zhou, K. & Guo, R. 2011. Research on Process Monitoring Method Based on SPC and PCA Technology. *IEEE Process Control Theory Applications*. 691–694.

Zhou, Y. & Forbes, J.F. 2003. Determining controller benefits via probabilistic optimization. *International Journal of Adaptive Control and Signal Processing*. 17:553–568.

Zwetsloot, I.. & Woodall, W. 2017. A head-to-head comparative study of the conditional performance of control charts based on estimated parameters. *Journal of Quality Engineering*. 29(2):244–253.

APPENDICES

APPENDIX A: PRELIMINARY AND CRITICAL SITE SURVEYS

Process operation

1. Current process flowsheet configuration/overview for the Concentrator plant.
2. Identification of any significant changes in flowsheet configuration implemented in the processing history of the plant.
3. The potential impact of flowsheet configuration changes on identified reference conditions: the operating conditions and economic performance.
4. Appreciation of captured process data.
5. Access to historical metallurgical and financial data.
6. Whether any previous work to relate key profit metrics such as the mineral recovery to corresponding operating conditions has been previously performed.
7. Whether any grind-float tests have been done for the Concentrator plant, for which a product particle size-mineral recovery relationship was developed as done in Edwards and Vien (1999).

Process control

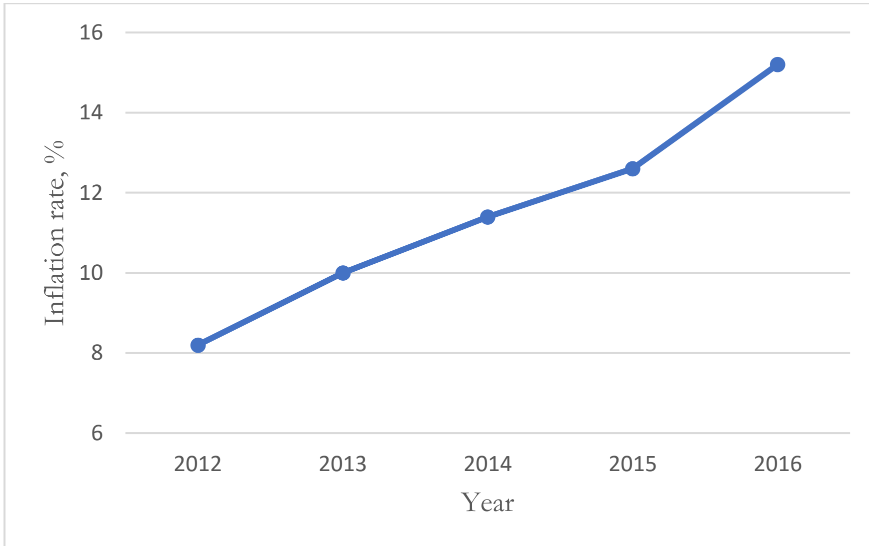
1. The control variables tracked per subsection of the Concentrator plant, how they are tracked and the tracking frequency.
2. How controlled variables can be ranked in terms of economic impact/significance.
3. How controlled variable set points and operating constraints are determined.
4. Objectives for the process control system and current methods for controller performance assessment.

Process economics

1. The type of economic data available for the Concentrator plant.
2. How operating costs for plant operations are distributed, and frequency of operating costs are acquisition and updating.
3. How the net concentrator revenue is determined, and profit quantified.

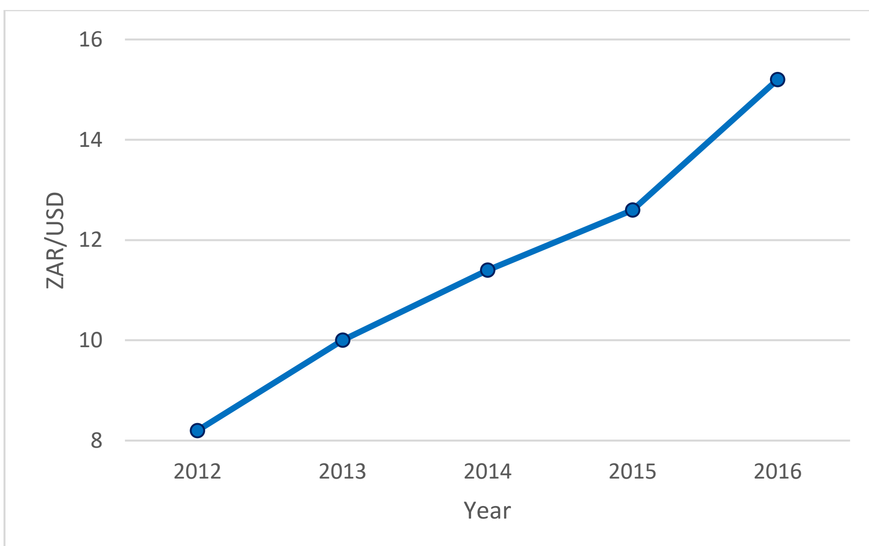
APPENDIX B: MARKET FACTORS INFLUENCING ECONOMIC PERFORMANCE

South African inflation rate



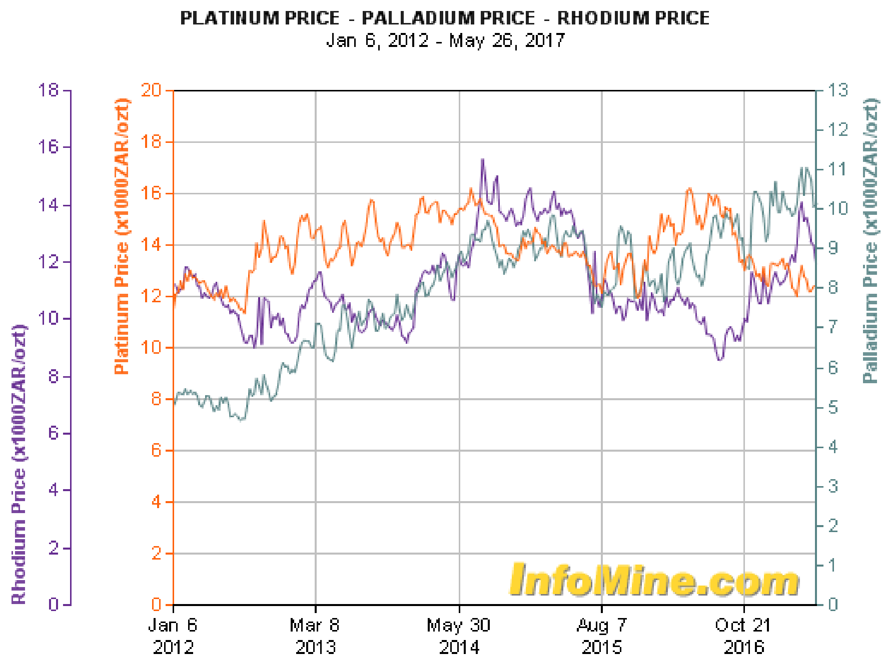
http://www.inflation.eu/inflation-rates/south-africa/historic-inflation/cpi-inflation-south-africa.aspx

Exchange rate movement



https://www.irs.gov/individuals/international-taxpayers/yearly-average-currency-exchange-rates

3E metal prices



http://www.infomine.com/ChartsAndData/ChartBuilder.aspx?z=f&gf=110577.USD.ozt&dr=5y&cd=1

APPENDIX C: CALCULATION FORMULAE

Normalizing

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad 1$$

where, x_{norm} is the normalized variable x

x_{max} is the maximum variable value

x_{min} is the minimum variable value

Amount of data available for analysis

$$D_{avail} = \frac{D_{analysis}}{s \times t \times C_{avail}} \qquad 2$$

where D_{avail} - amount of data available for analysis, years

$D_{analysis}$ - data to be analysed, shifts

s - conversion factor of 3shifts per day *t* - time conversion factor of 365 days per year

C_{avail} - average primary mill circuit availability. An average circuit availability of 90% is assumed based on historical plant availability statistics.

Sliding window size in shifts

$$w_{est} = \frac{2week \times \frac{7days}{week} \times 24hours/day}{8hours/shift} \quad 3$$

where w_{est} is the estimated window size, shifts

An estimated window size of 2 weeks is equivalent to 42shifts.

3E rougher flotation recovery

$$MR = \frac{(HG - T)}{100HG} \quad 4$$

where MR is the 3E mineral recovery, %

HG is the 3E head grade, g/t

T is the 3E rougher tail grade, g/t

3E basket price

$$BP = P_{adj}ER\sum_{x=1}^{3}(ep)_x \quad 5$$

where *BP* is the basket price, ZAR/oz

P_{adj} is the adjustment factor

ER is the exchange rate, USD/ZAR

x is each of the 3E metals

e is the prill split contribution

p is the metal price, USD/oz

Metal sales revenue

$$R = HG \times F \times MR \times t \times c \times \alpha \times BP_{adj} \tag{6}$$

where R is the 3E metal sales revenue (ZAR)

HG is the 3E head grade (g/t)

F is the throughput rate (t/h)

t is the time period (t)

MR - 3E rougher flotation mineral recovery (%)

c - oz/g conversion factor

BP_{adj} - adjusted basket price (ZAR/oz)

Electricity consumption

The total electricity consumption was derived for the primary ball mill, conveyor belts, flotation cell agitators and all pumps within the primary mill circuit, listed in **APPENDIX** E.

$$E_m = PRt \tag{7}$$

where Em is the primary ball mill electricity consumption, MWh

P is the average shift power, MW

R is the run time, %

t is the operating time, h

where

$$R = \frac{R_{act}}{R_{avail}} * 100\% \tag{8}$$

R_{act} is the actual running time, h

R_{avail} is the time ancillary equipment was available for operation, h

For each of the primary mill circuit ancillary equipment shown in **APPENDIX** E, the electricity consumption for each ancillary equipment was given as shown in Equation 5.0.

$$E_{anc} = \sum_{i=1}^{f} (IVRt)_i \qquad \mathbf{9}$$

where, E_{anc} is the ancillary equipment electricity consumption

f is the number of ancillary equipment

I is the current, amps

V is the voltage, volts

R is the runtime for each ancillary equipment, %

t is the operating time, h

The runtime was determined using rule based formula in MS Excel to determine the time ratio during which the equipment was actually running, to the total time available for operation during the month. The run time was determined as such in all of the following cases where relevant.

Electricity cost

The total electricity cost was determined as shown in Equation 6.0.

$$C_{elec} = ut(E_m + E_{anc}) \qquad 10$$

where, C_{elec} is the total electricity cost, ZAR

U_{elec} is the electricity unit cost, ZAR/kWh

t is the operating time, h

E_m is the primary ball mill consumption, kW

E_{anc} is the ancillary equipment electricity consumption, kW

Reagent cost

The runtime in this case was determined for each of the respective reagent dosage pump, and the total reagent cost was derived as below:

$$C_{reag} = \sum_{i=1}^{3} (c_{reag} u_{reag})_i \qquad 11$$

where, C_{reag} is the total reagent cost, ZAR

i is the reagent

c_{reag} is the reagent cost unit cost, ZAR/kg

u_{reag} is the number of units consumed, kg

$$C_s = c_s u_s \qquad 12$$

C_s is the steel ball grinding media cost, ZAR

c_s is the steel ball unit cost, ZAR/t

u_s is the number of steel ball units consumed, t

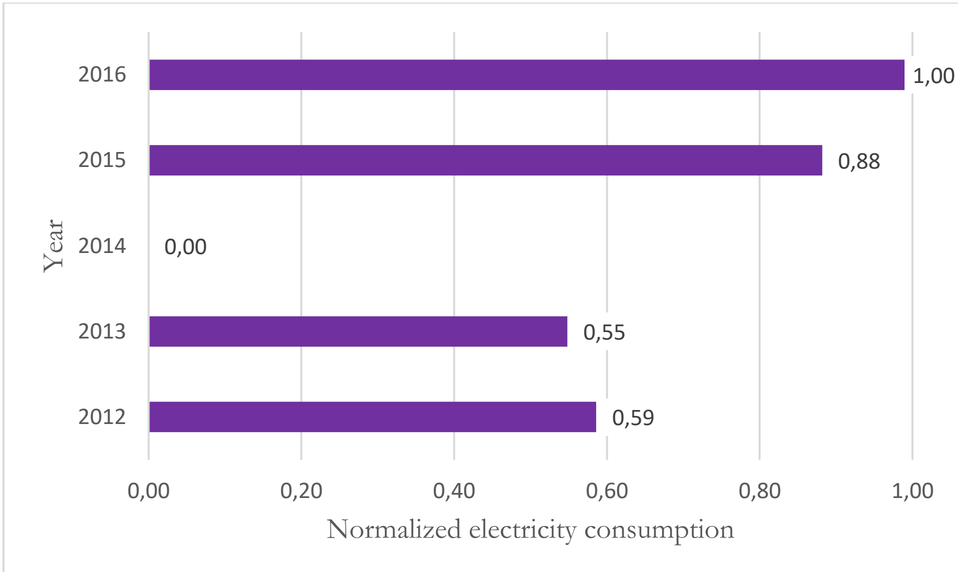
Total production cost

$$C_T = C_{elec} + C_{anc} + C_s \qquad 13$$

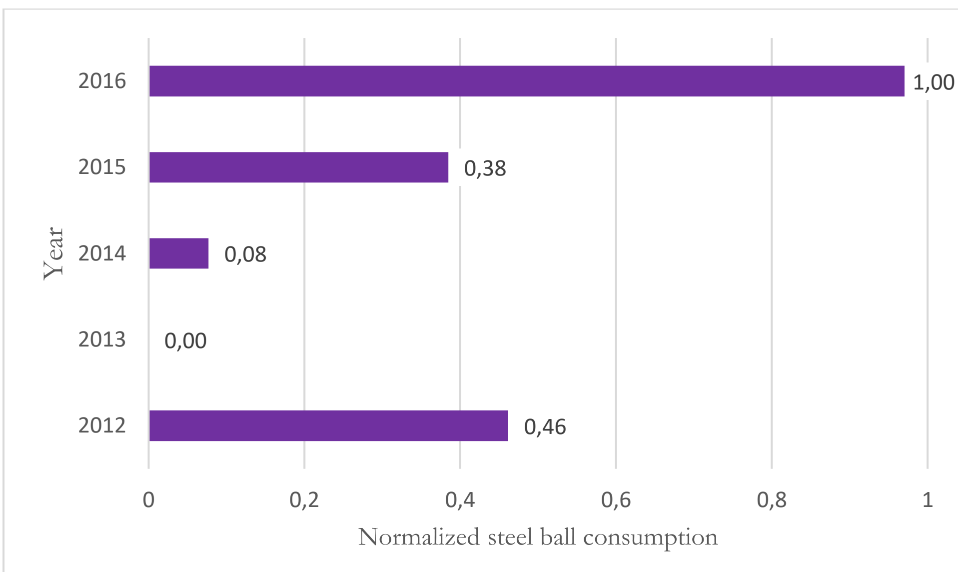
where, C_T is the total production cost, ZAR

APPENDIX D: NORMALIZED AVERAGE ELECTRICITY AND CONSUMABLE CONSUMPTION RATES

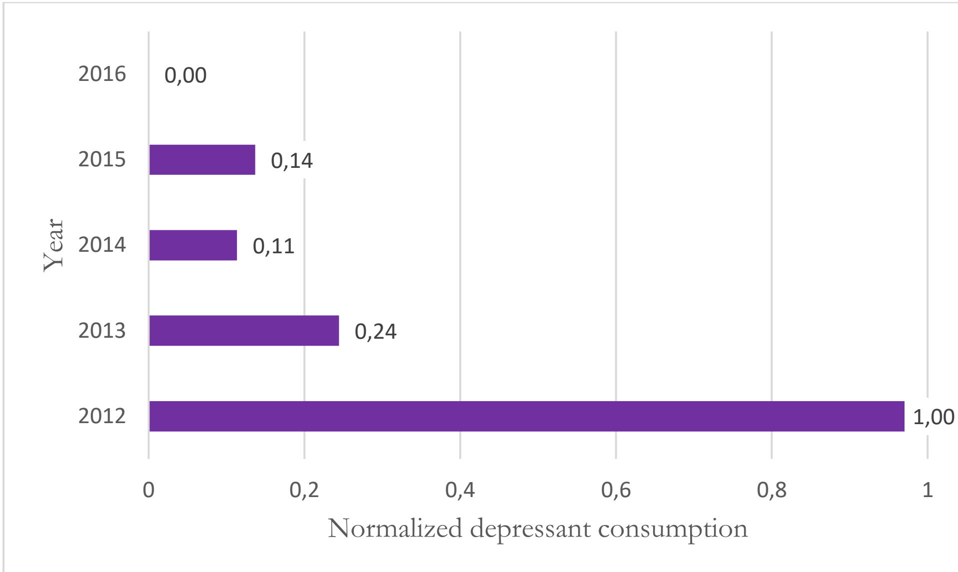
Average electricity consumption rate



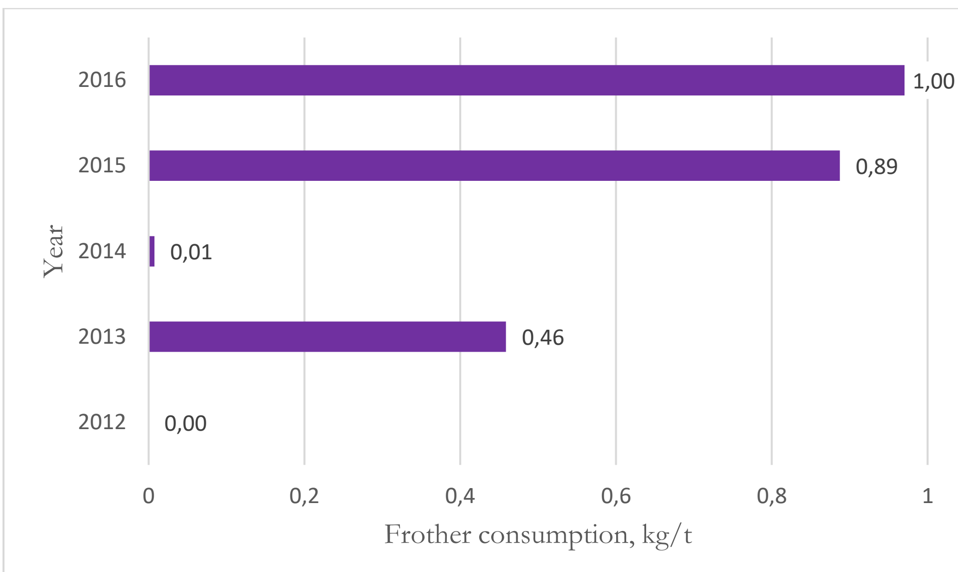
Average steel ball consumption rate



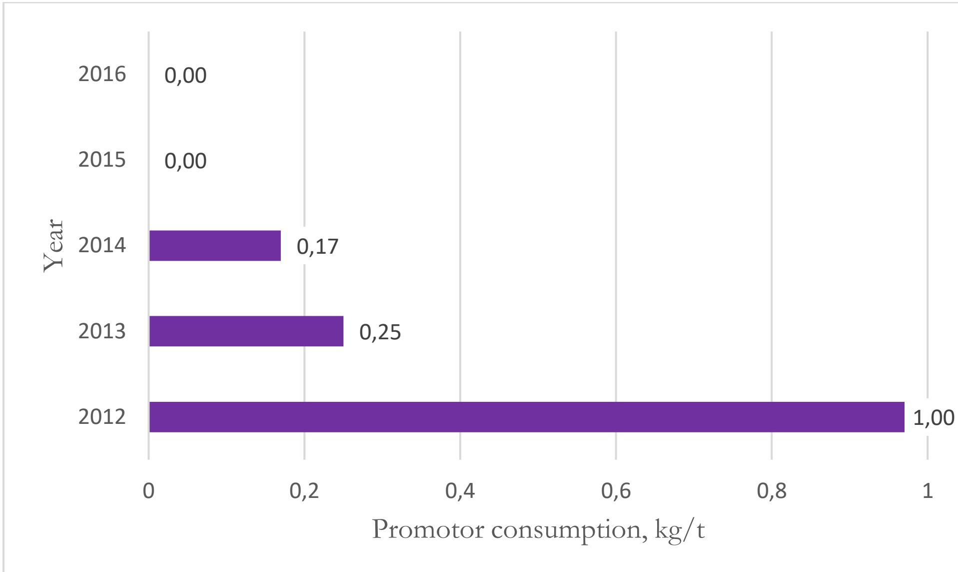
Average depressant consumption rate



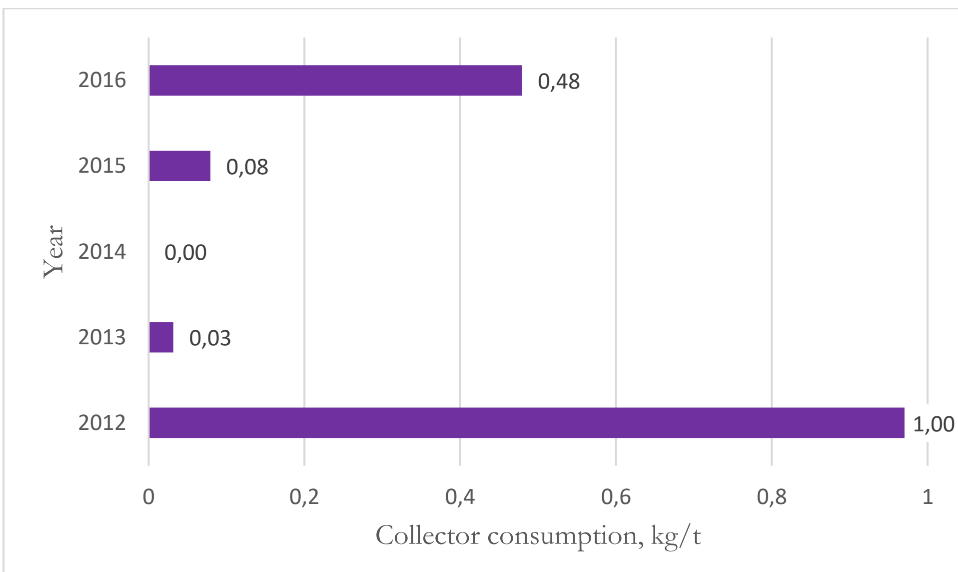
Average frother consumption rate



Average promoter consumption rate



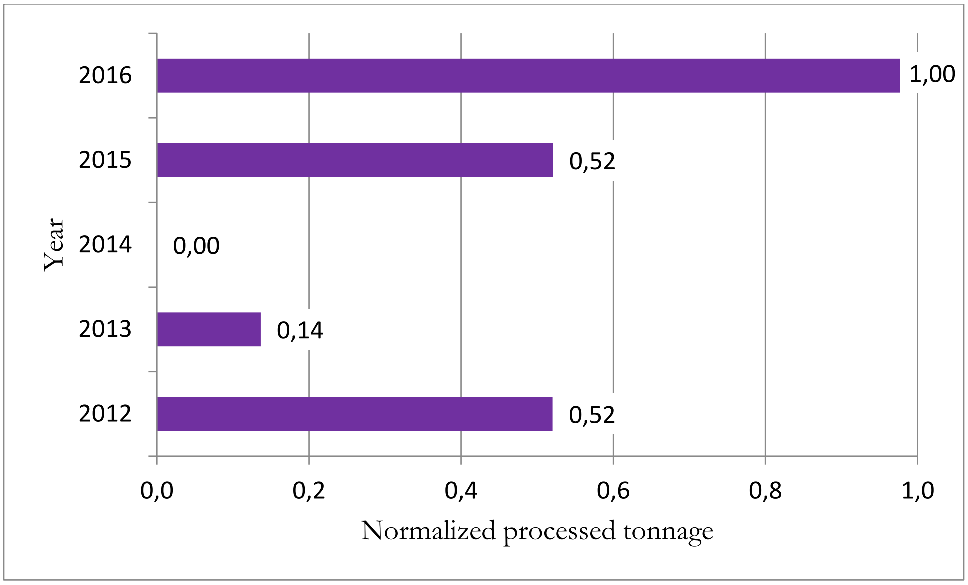
Average collector consumption rate



Appendix E: Ancillary equipment

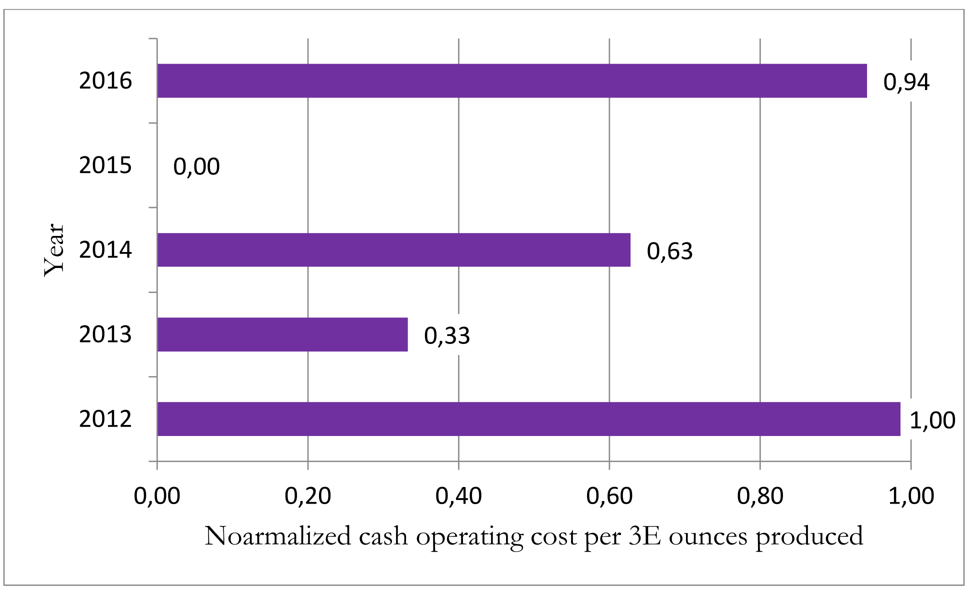
Ancillary equipment	
Flotation cells	
	Flotation cells 1-14 agitators
Conveyors	
	Primary mill feed conveyor
	Primary mill scats conveyor
Pumps	
	Primary mill sump
	1st grade rougher concentrate bank 1-2
	1st grade rougher agitator bank 1
	2nd grade rougher agitator bank 2
	2nd grade rougher concentrate bank 1-2
	Rougher bank spillage bank 1-2
	Rougher tails bank 1-2
	Frother dosage to rougher banks 1-2
	Depressant dosage to rougher banks 1-2
	Collector dosage to primary mill sump, rougher banks 1-2
	Promotor dosage to primary mill sump, rougher banks 1-2

Appendix F: Normalized average tonnage processed

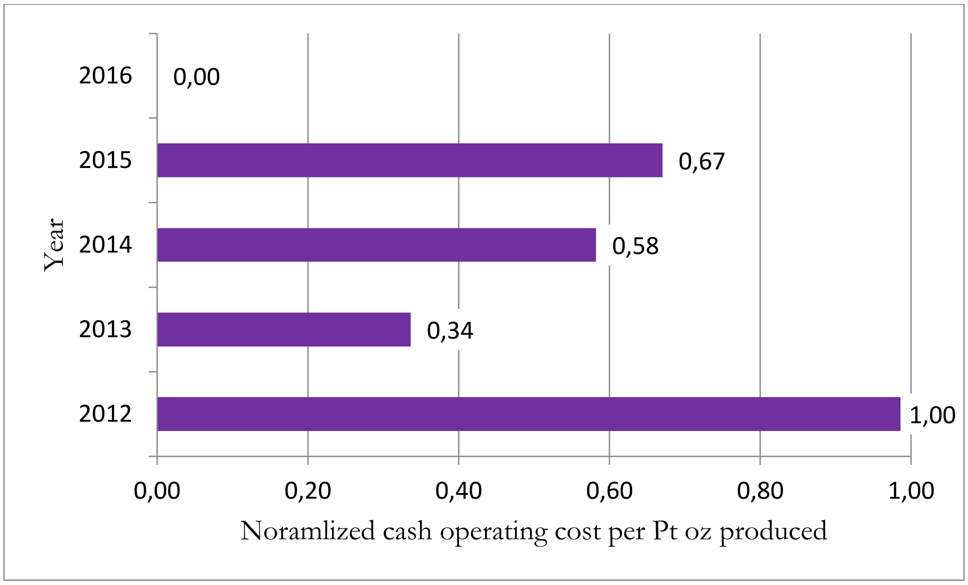


Appendix G: Normalized key performance indicators

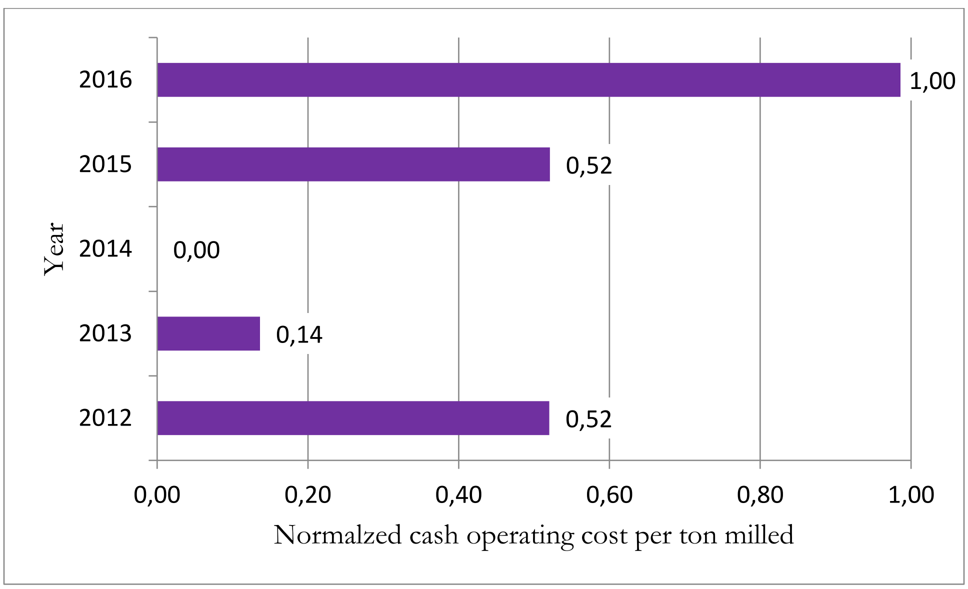
Average cash operating cost per 3E ounce produced



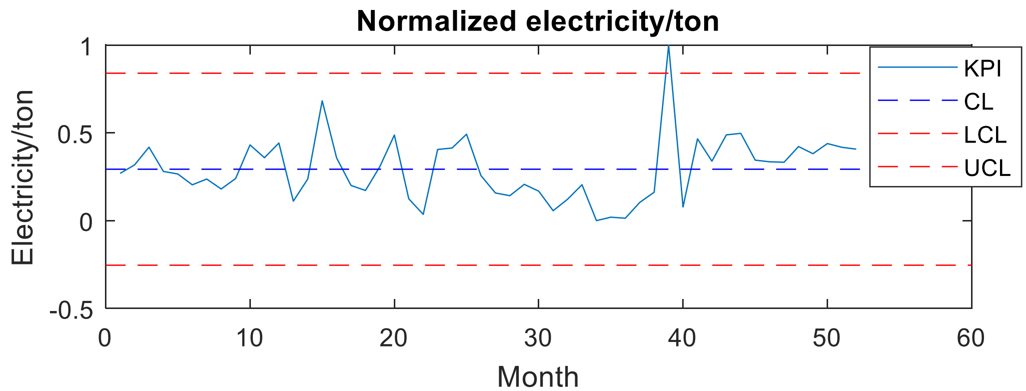
Average cash operating cost per Pt oz produced

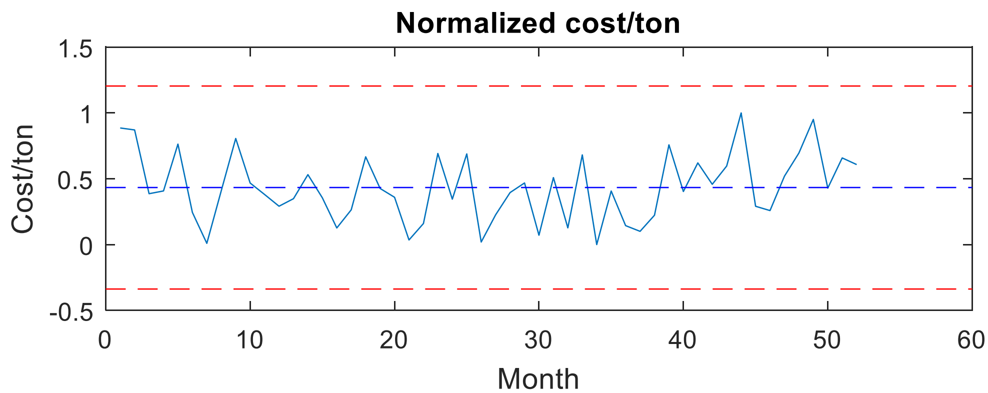


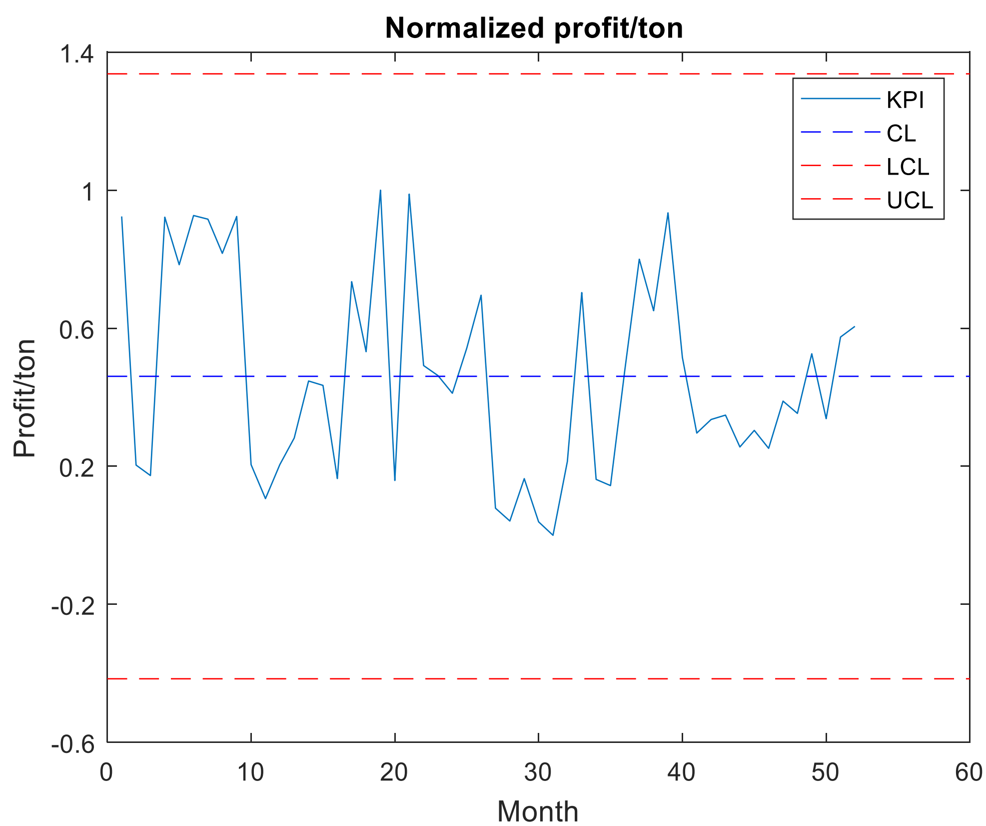
Average cash operating cost per ton milled

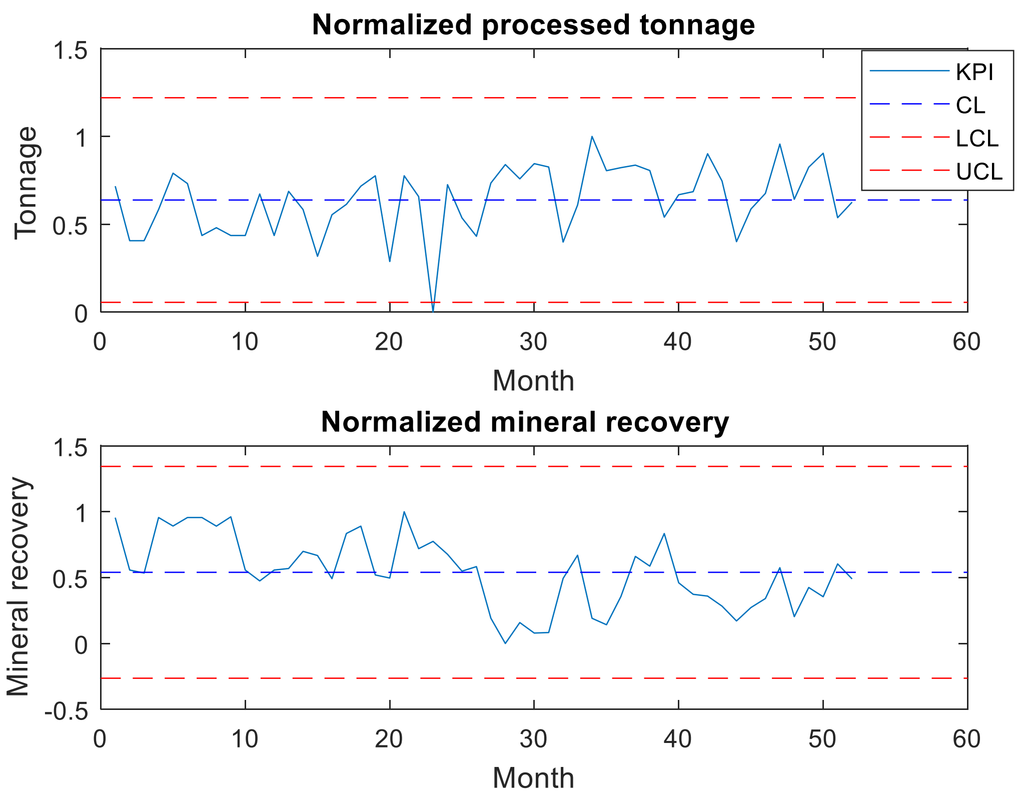


Appendix H : Monthly averages for key performance indicators



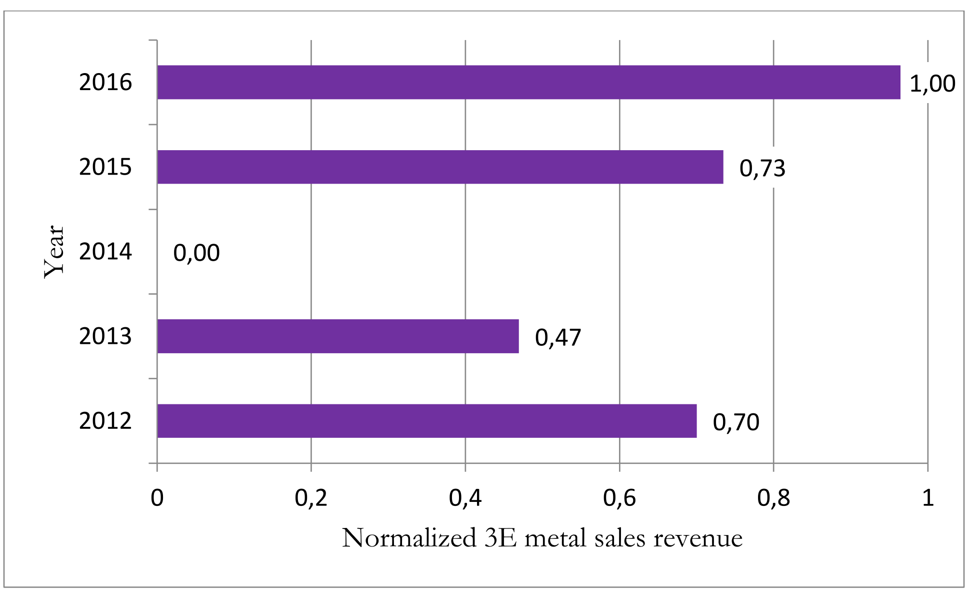




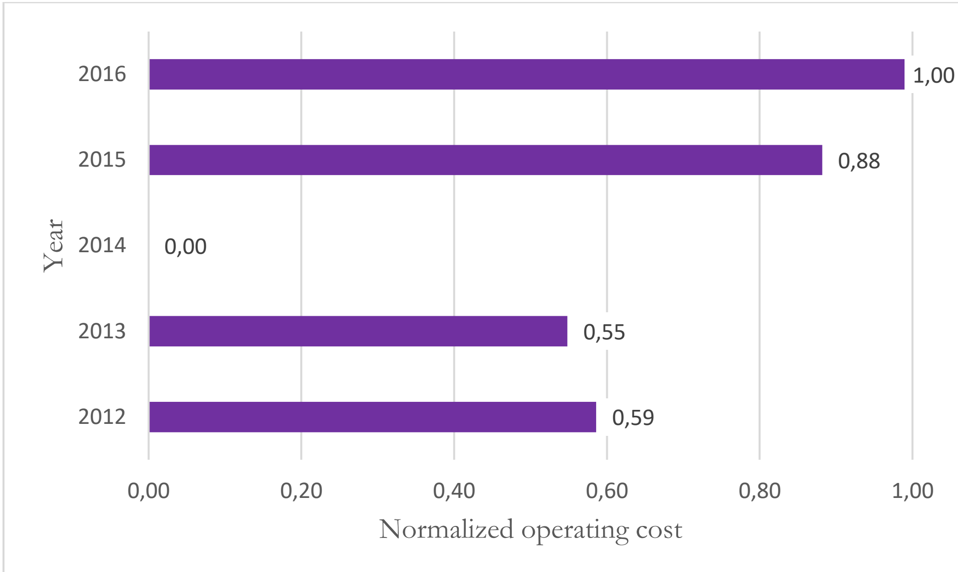


APPENDIX I: NORMALIZED PRIMARY MILL CIRCUIT ECONOMIC PERFORMANCE

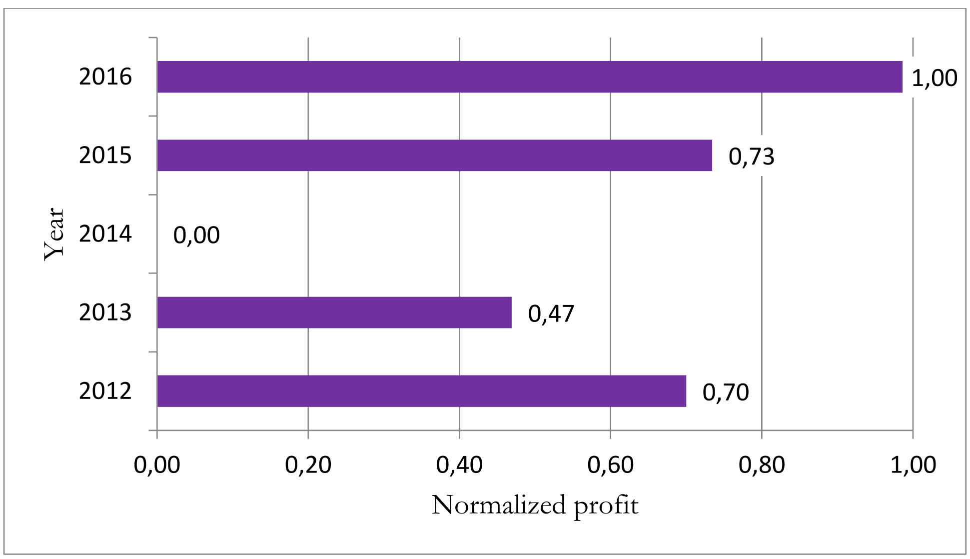
Average 3E metal sales revenue



Average operating cost



Average annual profit



APPENDIX J: SPOT METAL PRICES (AS AT JUNE 2016)

Element	Spot metal price (USD/oz)
Pt	976.00
Pd	545.00
Rh	660.00

Appendix K: Data of interest

Data item		Data source		Frequency of data generation	Data availability
Key controlled variables	Primary mill product PSD	Offline	Lab analysis data base	Every shift (8 hours)	48hours later
	Primary mill load	Online	Pi historian	Every second	Immediately
	Primary mill sump slurry density	Online	Pi historian	Every second	Immediately
	Rougher flotation mass pull	Online	Pi historian	Every second	Immediately
Metallurgical data	Tonnes milled	Online Offline	Pi historian Production reports	Every second Hourly (Control room report) Daily (Production report) Monthly (Production report) Monthly and yearly (Financial report)	Immediately Determined by report
	Head grade	Offline	Laboratory assaying	Every shift	48 hours later
	Rougher tails grade	Offline	Laboratory assaying	Every shift	48 hours later
	*Rougher flotation recovery	Offline	Computationally determined from	Based on available head and rougher tail grade grades	Not applicable

			available head and rougher tails grade		
Cost data	Actual motor current for the : Primary mill Primary mill circuit pumps Flotation cells Conveyor belts	Online and offline	Pi historian	Variable, based on predetermined data capture frequency	Not determined
	Motor voltage rating for the : Primary mill Primary mill circuit pumps Flotation cells and tank agitators Conveyor belts	Offline	Motor name plates	Not applicable	Not applicable
	Primary mill equipment running time	Online	Pi historian	Variable, based on predetermined data capture frequency	Immediately

	Reagent flowrate Depressant Collector Promotor Frother	Online	Pi historian	Variable, based on predetermined data capture frequency	Immediately
	Reagent concentration Depressant Collector Promotor Frother	Offline	Laboratory sampling	Every shift	24 hours later
	Primary mill steel ball grinding media	Offline	Control room log sheet Financial report	Every shift Monthly	8hours later Every first week of the new month
	Unit prices for cost data	Offline	Unit prices from April 2016 report	Not applicable	Not applicable
*Revenue data	Basket price Metal pricing Exchange rate	Offline	Computationally determined from current prill split and commodity prices www.kitco.com www.xe.com	Calculated	

APPENDIX L: MATHEMATICAL MODEL FOR SAG MILL

Feeder module

$$V_{fwo} = MIW$$

$$V_{fso} = \frac{MFS}{D_s}(1 - \alpha_s)$$

$$V_{ffo} = \frac{MFS}{D_s}\alpha_f$$

$$V_{fro} = \frac{MFS}{D_s}\alpha_r$$

$$V_{fro} = \frac{MFB}{D_B}$$

Mill module

$$\frac{d}{dt}X_{mw} = V_{mwi} - V_{mwo}$$

$$\frac{d}{dt}X_{ms} = V_{msi} - V_{mso} + RC$$

$$\frac{d}{dt}X_{mf} = V_{mfi} - V_{mfo} + FP$$

$$\frac{d}{dt}X_{mr} = V_{mri} - RC$$

$$\frac{d}{dt}X_{mb} = V_{mbi} - BC$$

Mill Discharge

$$\boldsymbol{V_{mwo} = V_v \times \varphi \times X_{mw} \times \frac{X_{mw}}{X_{ms} + X_{mw}}}$$

$$\boldsymbol{V_{mso} = V_v \times \varphi \times X_{mw} \times \frac{X_{ms}}{X_{ms} + X_{mw}}}$$

$$\boldsymbol{V_{mfo} = V_v \times \varphi \times X_{mw} \times \frac{X_{mwmf}}{X_{ms} + X_{mw}}}$$

$$\boldsymbol{V_{mro} = V_{mbo} = 0}$$

Sump Module

$$\frac{d}{dt}X_{sw} = V_{swi} - V_{swo} + SFW$$

$$\frac{d}{dt}X_{ss} = V_{ssi} - V_{sso}$$

$$\frac{d}{dt}X_{sf} = V_{sfi} - V_{sfo}$$

Sump Discharge

$$V_{swo} = CFF \times \frac{X_{sw}}{SVOL}$$

$$V_{sso} = CFF \times \frac{X_{ss}}{SVOL}$$

$$V_{sfo} = CFF \times \frac{X_{sf}}{SVOL}$$

Hydrocyclone module

Hydrocyclone Underflow

$$V_{cwu} = \frac{V_{cwi}(\boldsymbol{V_{ccu} - F_u V_{ccu}})}{F_u V_{cwi} + \boldsymbol{F_u V_{cfi} - V_{cfi}}}$$

$$V_{cfu} = \frac{V_{cfi}(\boldsymbol{V_{ccu} - F_u V_{ccu}})}{F_u V_{cwi} + \boldsymbol{F_u V_{cfi} - V_{cfi}}}$$

Hydrocyclone Overflow

$$\boldsymbol{PSE} = \frac{\boldsymbol{V_{cfi}} - V_{cfu}}{V_{cci} + \boldsymbol{V_{ccu} - V_{cfo}}}$$

Flotation

The mathematical descriptions are shown below:

V denotes the flowrate, m^3/h

X denotes the states of the model as volumes, m^3

RC is the rock consumption

BC is the ball consumption

FP is the fines production

α denotes the fraction

ϕ is the rheology factor

Subscripts

The first subscript indicates the module considered

The second subscript specifies one of the five states

The last subscript shows an inflow (i), outflow (o) or underflow (u)

The connotations are given in the Table below:

Subscripts for Le Roux's model

Subscript	Description
$X_{\Delta -}$	f-feeder m-mill s-sump c-cyclone
$X_{-\Delta}$	w-water s-solids c-coarse f-fines r-rocks b-balls t -total
$V_{--\Delta}$	i-inflow o-outflow u-underflow

APPENDIX M: STEEL BALL – POWER RELATIONSHIP

$$BC = \frac{P_{mill}\boldsymbol{\varphi}}{\phi}\left(\frac{X_{mb}}{D_s(X_{mr}+X_{ms})+D_B X_{mb}}\right) \quad 14$$

where, BC - steel ball grinding media consumption, t

P_{mill} - power draw, kW

φ - steel abrasion factor, kWh/t

ϕ - rheology factor,

X_{mb} - ball charge fraction

D_s - density of steel balls, t/m^3

D_B - density of feed ore, t/m^3

X_{mr} - rock fraction

X_{ms} - solids fraction

APPENDIX N: SIMULATION EXPERIMENT CALCULATIONS

Mineral recovery from particle size

$$PR_i = -0.009776({PS_i}^2) + 1.705(PS_i) - 2.995 \qquad \textbf{15}$$

Average predicted mineral recovery

$$PR_{ave} = \sum_{i=1}^{m} f_i \, PR_i \qquad \textbf{16}$$

where, PR_{ave} - shift potential mineral recovery

f_i - fraction of data in the bin i

PR_i - potential recovery derived from Equation 15 for bin i

m - number of intervals in the frequency distribution

The fraction of the data in bin i is derived as shown in Equation **17.**

$$f_i = \frac{f}{f_t} \qquad \textbf{17}$$

Where f - number of data in bin i

f_t - total number of data points

Number of bins

$$S = \max(PR) - \min(PR) \qquad \textbf{18}$$

Where S is the range

$$N = \frac{S}{Bw} \tag{19}$$

Where N - number of bins

Bw – bin width

Bin width calculation

$$Bw = 2 \times IQR(THR) \times n^{-1/3} \tag{20}$$

where *IQR* – interquartile range

THR – throughput

n – sample size

EPI calculation

$$EPI = \left(k \sum_{1=1}^{m} \sum_{j=1}^{s} f_{i,j}\, P_{i,j}\right) - \sum_{e=1}^{n} (cu)_e \tag{21}$$

Where *i* - shift potential mineral recovery PDF (%)

j - mill throughput PDF (tph)

f - frequency for class widths, *i,j*

P - class interval median for the class *i,j*

m, s - the number of bins for the PDF *I, j*

c -number of cost element units consumed (units)

u - cost element unit price (ZAR/unit)

e - cost element

n - number of cost elements

$$k \;=\; HG \times BP_{adj} \tag{22}$$

Where HG - head grade of 3g/t (adopted from Matthew & Craig (2013).

BP_{adj} - adjusted basket price (ZAR/oz) derived as shown in Equation 23 (Appendix N)

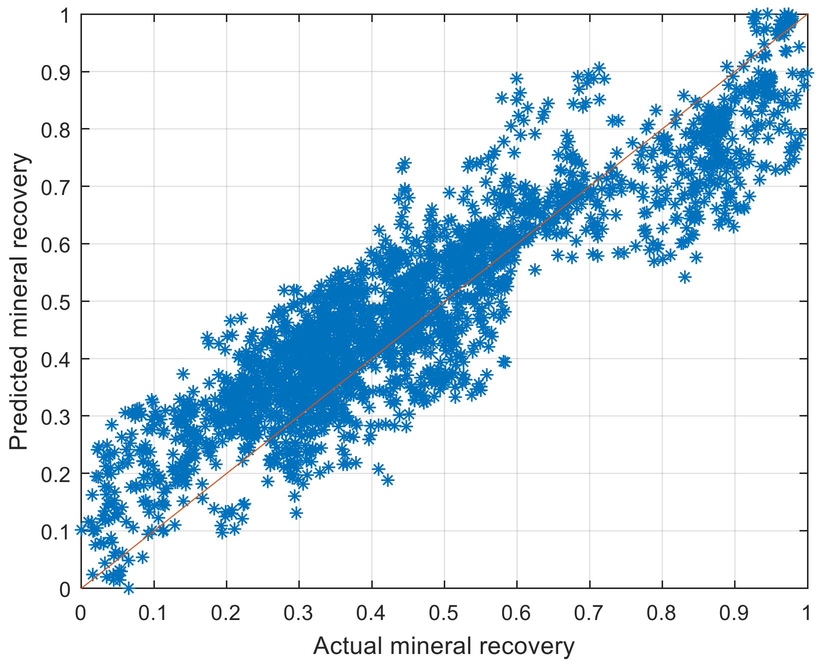
0.032 - a conversion factor of between grams and troy ounces.

0.75 - an adjustment factor of was assigned for a PGM operation by Matthew & Craig (2013).

BP is the basket price adopted from industrial prill split data (ZAR/4E oz)

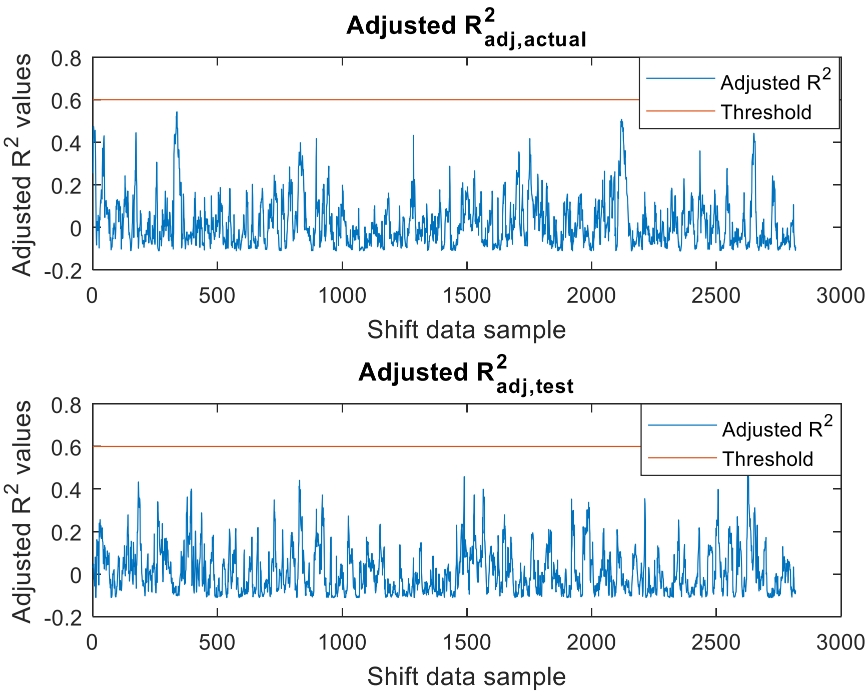
APPENDIX O: PLOTS FOR ACTUAL VS. PREDICTED MINERAL RECOVERY

Multi-predictor PVA approach



APPENDIX P: RESULTS FOR WINDOW SIZE 21

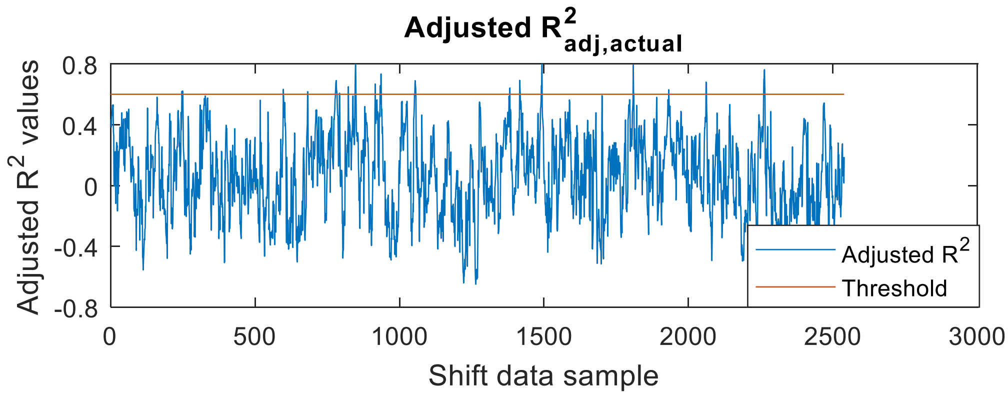
Single-predictor PVA approach – searches for EPFs

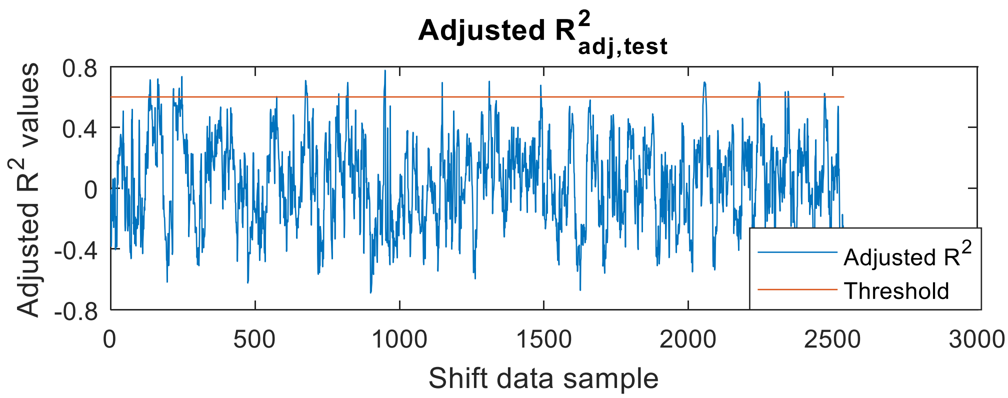


Results summary

Single-predictors PVA	
Maximum $R^2_{adj,actual}$	0.54
Maximum $R^2_{adj,test}$	0.47
$R^2_{adj,actual}$ above threshold	0
$R^2_{adj,test}$ above threshold	0

Multi-predictor PVA approach – searches for EPFs





Results summary

Multi-predictor PVA	
Maximum $R^2_{adj,actual}$	0.856
Maximum $R^2_{adj,test}$	0.78
$R^2_{adj,actual}$ above threshold	57
$R^2_{adj,test}$ above threshold	41

Appendix Q: Average mineral recovery for simulated faults

Experiment Number	Drifting load cell	Steel ball quality	Ore hardness
1	58.20	70.25	68.34
2	56.70	69.15	67.23
3	54.50	72.05	66.25
4	59.40	68.15	69.01
5	55.10	71.12	64.21

APPENDIX R: AVERAGE MILL THROUGHPUT FOR SIMULATED FAULTS

Experiment Number	Drifting load cell	Steel ball quality	Ore hardness
1	39.13	32.53	28.86
2	37.15	31.61	27.44
3	36.00	28.79	26.51
4	34.12	33.52	30.73
5	40.01	30.25	29.14