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Performance Audit of a Semi-autogenous Grinding Mill Circuit

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Abstract: The paper proposes a novel performance audit report for a SAG Mill Circuit. The audit report is demonstrated on a validated run-of-mine ore grinding circuit model, which the authors have captured in a simulator, using Simulink. The elements of the report combine established statistics and views with specific mill control context. A representative case study demonstrates the construction and interpretation of the audit report, so as to gain insight into the circuit performance over a historical data episode.

Key words: Grinding mills, statistical process control, fault diagnosis, control performance

1. INTRODUCTION

Operational problems: One cannot escape them. So, one learns to see a problem coming; often, from past experience. The monitoring and audit of historical process data can be a very effective way of learning from past experience.

The monitoring of process systems in mineral processing and other materials manufacturing plants may target several variables, such as key performance indicators (KPIs), important process variables related to process efficiency and potential hazards, as well as control performance (e.g. settling times and manipulated variable saturation). The purposes of process monitoring may include short-term detection and identification of abnormal conditions, so as to allow automated or manual process recovery; or long-term identification of opportunities for continuous process improvement.

Presenting a sensible, insightful overview of a large number of measured variables can be achieved by focusing on a selection of relevant key performance indicators, as well as by means of multivariate statistical process control charts (MSPC) and latent variable methods, such as principal component analysis (PCA) and partial least squares (PLS) (MacGregor and Kourti, 1995; MacGregor et al. 2007).

The varying goals of process monitoring can be accommodated by publishing context-specific monitoring reports to appropriate personnel, at appropriate time-scales. The complex relations between variables may be expressed in a monitoring report, by including an overview of changing correlations between process variables.

In minerals engineering, and communition in particular, the semi-autogenous grinding mill (SAG mill) is an operational unit where many problems may lurk. A suitable overview of historical data should prove useful, indeed (Remes et al. 2006).

This study considers a novel process monitoring overview for a generic semi-autogenous grinding (SAG) mill circuit. Since the goal of such a process monitoring overview is a succinct evaluation of the performance of the considered process system, this overview is termed a performance audit.

The organisation of this paper is as follows: Section 2 presents an overview of SAG milling circuit monitoring and control requirements; Section 3 discusses the elements of the performance audit; Section 4 treats a general dynamic simulation for a SAG milling circuit; Section 5 considers a case study illustrating the performance audit on a SAG milling circuit simulation; and overall conclusions and future developments follow in Section 6.

2. SAG MILLING CIRCUIT OVERVIEW

Amongst the problems that face SAG milling operations are ore feed inconsistency, energy inefficiency, instability of operating point, and particle size of grind output. Increasing economic pressure to raise throughput only serves to aggravate these existing problem areas.

The dominant objective for control of grinding mill circuits is maximising of economic benefit. According to a survey on the control and economic concerns of grinding mill circuits (Wei and Craig, 2008), the main contributors to this benefit are gains in process stability, throughput, and energy efficiency.

Several control strategies are followed, including advanced process control; yet, more than 60% of grinding circuits still rely on some form of PID control, according to Wei and Craig (2008). The question at the root of this paper is: What significant insight can a comprehensive audit report on historical operational data provide into the behaviour of a chosen control strategy, over and above conventional trend monitoring?

This paper proposes a methodology to produce and interpret a performance audit report on a SAG mill. The audit report will contain context-specific views on the important measured variables of the SAG mill, such that these views reveal interesting events and trends that may form a basis for improving control strategy.

2.1 A grinding mill circuit

In the typical grinding mill circuit that deploys a SAG mill, the mill is accompanied by a sump and a process recycle loop that includes a hydrocyclone (Figure 1).

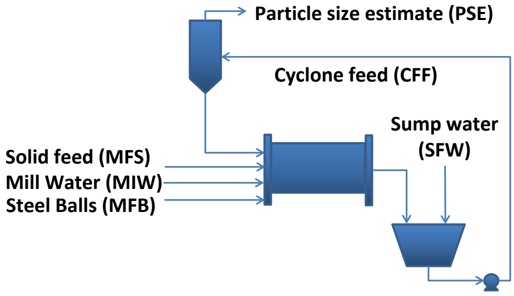

Figure 1: SAG mill circuit diagram (Coetzee, 2009)

Mill input material consists of ore, recycled grind product and water. The mill content forms slurry that exits as mill product into the sump, which acts as a buffer.

The mill feed is augmented with steel balls that assist the fracturing of larger ore particles through interparticle impact. Complex internal dynamics combine impact and shear forces to fracture and grind down particles.

Mill product is classified by the hydrocyclone into overflow and underflow, viz. particles that are smaller or equal to specification in size, and particles that are larger than specified size, respectively. The underflow is fed back into the mill for further grinding.

Water is added to the mill and sump to condition and control the grinding process (Coetzee, 2009). The mill load and sump level are open-loop unstable, and must be controlled, since the mill and sump act as integrators in the process recycle circuit (Craig et al., 1992).

An optimal operating range of mill load prevails that includes a critical point, beyond which the mill must be stopped and manually unloaded. Such intervention is costly and carries high risk of operator injury.

This study focuses on a SAG mill circuit that implements three PI controllers, viz. particle size – cyclone slurry feed-rate loop; mill load – mill ore feed loop; sump level – sump water feed-rate loop.

2.2 Important Grinding Mill Variables

The following controlled process variables (PV's) are listed in order of importance by respondents in the survey by Wei and Craig (2008):

1. Slurry level in sump
2. Product particle size
3. Sump discharge slurry density
4. Feed ratio (solids to water into mill)
5. Mill load

The following manipulated process variables (MV's) are listed in the same survey:

1. Flow rate of water to sump
2. Flow rate of water to mill
3. Feed rate of solids to mill
4. Flow rate of slurry from sump

Key interdependencies between variables include the following:

1. Mill load and mill power
2. Particle size and mill load
3. Particle size and density of sump discharge

2.3 Monitoring of milling circuit performance

The primary challenge for process monitoring lies in how best to turn observability into insight for the sake of process improvement. In this arena, context is king.

The approach of this study to monitoring the performance of a SAG mill adopts the control strategy as context. One can pick from several possible control strategies, given a control objective, which in itself requires careful consideration. Monitoring the historical performance of the selected control strategy can bring insight in support of future improvements.

One conventional view of mill performance plots mill power against load. This view can overlay the characteristic mill power-load curve, provided a valid curve is available. However, this view cannot monitor further, important interdependencies, e.g. particle size and mill load, as well as particle size and sump discharge density.

In fact, views constructed of other multivariate combinations, taken from the list of important variables under Section 2.2, may yield additional insight. Such views are investigated in the remainder of this paper.

3. PERFORMANCE AUDIT ELEMENTS

The following elements are proposed for a performance audit of a SAG milling circuit:

a) SPC on KPI's Particle Size Estimate and Specific Power

Statistical process control offers a direct view of a single variable over a fixed time window. For the audit, the two most important KPI's were selected, with any deviation further than three standard deviations from the training data mean being flagged as a possible fault.

If the PSE deviates significantly, it has a large effect on downstream process efficiency, e.g. flotation cell recovery.

Specific power (mill power draw divided by product throughput) gives a direct indication of how efficiently the mill is operating. High specific power would indicate improper mill loading, water addition or an increase in ore hardness.

b) Power-Load Density Plot

For the performance audit, a density plot is created showing the most visited regions, as well as the trajectory between points. This view offers insight into mill efficiency.

The power load curve is a traditional representation of mill performance. Normally, the mill power draw is maximised at a certain volume loading – representing the most effective milling point. If the mill is overloaded too far past this point, it becomes ineffective and may need to be manually discharged. Operating at the lower load end signals an ineffective use of mill power, leading to higher production costs. The power-load density plot could be augmented by a corrected power-load curve, where a regression model (e.g. neural network model) is used to predict the power-load curve from measured process variables, compensating for the effect of varying operating conditions (see Aldrich et al., 2014 for more details).

c) Mill State Density

In addition to the univariate SPC analyses, a multivariate representation of the data was also created, using PCA. PCA allows one to combine the process variables, in terms of a subset of composite principle components that explains the significant variance of the process variables. In doing so, linear variable relationships are captured, which forms a basis to project new operational data and find differences to the (baseline) training data.

For the milling audit report, PCA was performed on all the important measured variables, so as to create a mill state density plot and two diagnostic statistics, namely squared prediction error (SPE) and the modified Hotelling's T^2 statistic, which show the deviation of each point from the assumed lower dimensional manifold and from the expected normal operating centroid (given that the training data variance structure holds), respectively. This view and these statistics can be used to determine whether a fault may have occurred and offer a starting point for root cause analyses. The application to SAG mill monitoring with PCA has also been considered by Ko and Shang (2011). Their study indicated that PCA is a suitable approach to visualize overall mill process performance, as well as to detect abnormal process conditions. Aldrich et al. (2014) also considered visualization of mill circuit time series data, but for the purpose of controller state tracking, making use of embedded mill variables.

d) Correlation Plot of detected fault

The correlation plot of the data included all the important measured variables for a given fault episode. The correlations could indicate changes in key interdependencies. The limits on the correlation values were determined via bootstrapping by investigating various contiguous sets of data (with the same amount of samples) in the training episode. Although bivariate correlations do not capture the full complexity of multivariate interdependency, identifying major shifts in bivariate correlations may assist in further root cause analysis.

e) SPE Contribution Plot

In the SPE contribution plot the contribution of each variable to the overall SPE diagnostic is presented. These contributions may help identify important variables associated with fault causes and symptoms.

f) Manipulated Variable Saturation

A major focus of the mill performance audit is aimed at controller performance. By tracking how saturated the manipulated variables are, one can determine whether the process is being operated within acceptable limits. Certain manipulated variables need to be run closer to saturation, e.g. ore feed (increasing productivity), while others may be minimised to decrease resource usage (e.g. sump water). Saturation plots also allows one to track the largest variations, so as to see how well controllers react to process disturbances.

g) Set Point Tracking

Finally, the set point tracking of the controllers were quantified by calculating the error of each controlled variable datum, with relative limits generated, again using three sigma deviations from the training data.

4. SAG MILL CIRCUIT SIMULATION

4.1 Model Baseline

A newly validated run-of-mine ore grinding circuit model (Le Roux et al., 2013) was used for design and testing of the mill monitoring solution. This model had been used before by various authors (Craig, 2012; Coetzee, 2009; Coetzee, et al., 2010), specifically for advanced controller development.

The model, which accounts for rheology, power load, different breakage mechanisms, had been developed to offer a simple and theoretically sound representation of the milling circuit, and avoided a large, empirically-fitted set of parameters.

The first step was to recreate the Le Roux model in Simulink from published differential and state equations (Le Roux, et al., 2013). During validation, Le Roux et al. (2013) used collected survey data to drive the model and then compared the model outputs to that of the survey. Figure 2, below, shows that the current Simulink implementation has successfully replicated the work of Le Roux et al. for various survey data.

4.2 Controllers

As mentioned in Section 2.1, the milling process contains open-loop unstable units. Therefore, any simulation with realistic process inputs also will require realistic controllers, to keep the process within desired limits. The focus of this paper is the creation of a general mill monitoring solution, to investigate mill performance. Since more than 60% of milling operations used PI control, it was selected as a base case controller in this study.

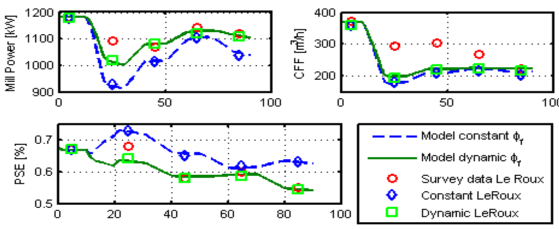

Figure 2: Recreated model against model and survey data from Le Roux et al. (2013)

In order to ensure sensible controller design, the PI control loops proposed by Coetzee (2009), for the same model as Le Roux et al. (2013), were chosen and retuned.

5. CASE STUDY

The milling case study consists of two data sets: normal operating condition (NOC) and disturbance (fault) data. Typically, NOC data should span all input variation expected during acceptable operation, i.e. where no large disturbances were present and the mill operation was close to optimal. The fault data reveal an input disturbance that occurs in real world plants and causes sub-optimal milling performance.

Careful selection of the NOC and fault data is critical, so as to create a sensible monitoring solution. If the NOC data contain too few process excitations the monitoring solution will be too sensitive and will alarm on virtually any new data. The converse of too large NOC process excitations will result in a solution that cannot pick up significant abnormalities.

5.1 Normal Operating Conditions

For the NOC data, it was decided to err on the side of a larger spectrum of process inputs, by selecting the Le Roux (2013) collected survey data inputs as process drivers. Furthermore, additional process noise was added, by introducing random steps in various process variables, as proposed by Coetzee et al. (2010). These variables included ore hardness, ore feed size distribution, and coarse split in the hydrocyclone. Each of the above variables was taken from a uniform distribution every 120s, to ensure NOC data included continuous small process disturbances.

5.2 Operating Disturbance

When choosing a suitable disturbance for this study, the major considerations are process impact, real world occurrence and available measurements. Ideally, the disturbance should have a definite impact on the process, not be easily measured, and occur often enough to be important to daily operations.

Ore feed hardness was chosen as an operational disturbance. Ore hardness has a significant impact on milling operation (mainly, increasing power needed for grinding), occurs in real-world processing and is typically not measured online during milling operation (Cuevas and Cipriano, 2008). Hardness disturbances may occur when switching from one mining face to another or even in a single mine face. The selection of the disturbance magnitude followed previous selections by Coetzee (2010) and Craig (2012), viz. a magnitude increase of 50%.

5.3 Generating the Audit Report

A MATLAB implementation was created of the monitoring methodology proposed in Section 3, and combined with the Simulink model, so as automatically to simulate and then process the milling circuit data for a range of disturbance magnitudes. The resulting audit report appears on the next page, as a collage of figures.

5.4 Interpretation of Audit Report

It is important correctly to interpret the performance elements described in Section 3. A hierarchical approach that flows from Figure 3 to Figure 11, shown on the following page, is proposed. The first figures are designed quickly to show detected errors, while consequent figures attempt to add context to these errors. The selected data episode experienced a 50% increase in ore feed hardness at the 50 minutes mark.

Mill state density

The mill state density plot, Figure 6, offers a combined view of all the data and is, therefore, an ideal starting figure. Note the added ellipse enclosing the 99% percentile Hotelling's T^2 limit of the training data, based on two retained principal components (66% of total NOC variance). It is apparent that a significant portion of the data episode falls outside of this ellipse. In particular, two distinct clusters are visible, suggesting a definite process state change has occurred within the episode. In order to confirm the states, the SPC and statistics plots may be investigated.

SPC and diagnostic statistics

The SPC (Figure 3) and diagnostic statistics (SPE, Figure 5, and Hotelling's T^2, Figure 7) substantiate that large abnormalities have been observed in the new data. Each of the figures, with the exception of the PSE SPC plot, shows multiple and consistent fault detection beyond the 100 min mark. The Hotelling's T^2 statistic gives the earliest event detection, at 61 min, while both SPC plots and the SPE statistic detect error events only at 80min-90min. Notably, at 61 min, PSE and specific power measurements are still well within normal operating conditions. Figure 5 and Figure 7 show a drastic increase in detected events after ±70min, corresponding to the two clusters seen on the mill state density plot.

Fault data correlation and SPE contribution plot

Figures 8 and 9 are presented to give an overview of changes in key interdependences, as well as to assist in the interpretation of the SPE diagnostic statistic. The correlation plot indicates that the following bivariate correlations have changed significantly: MFS-MillPower, SFW-CFF and SVOL-Throughput. Since the MFS-Load correlation has not changed significantly, the mill control loop can be assumed to still be operating as desired. The change in MFS-MillPower correlation (given a functioning mill control loop) may suggest a change in grinding efficiency, which is consistent with an increased hardness disturbance. The SFW-CFF and SVOL-Throughput correlation changes may

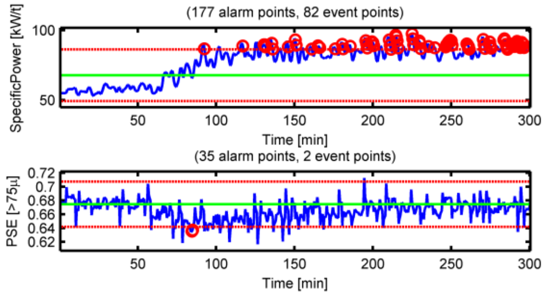

Figure 3: Statistical process control on KPI variables

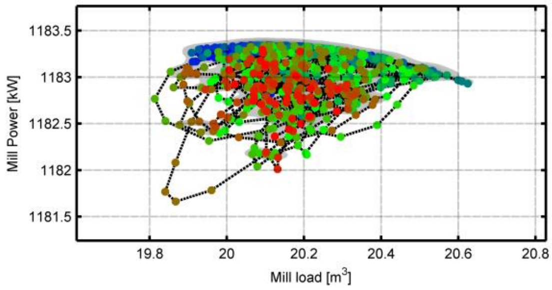

Figure 4: Power-load density plot

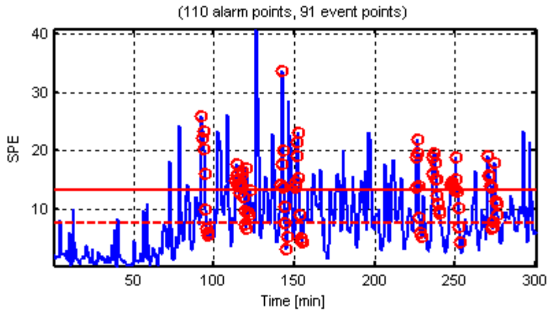

Figure 5: Squared prediction error (event logged after three consecutive alarms)

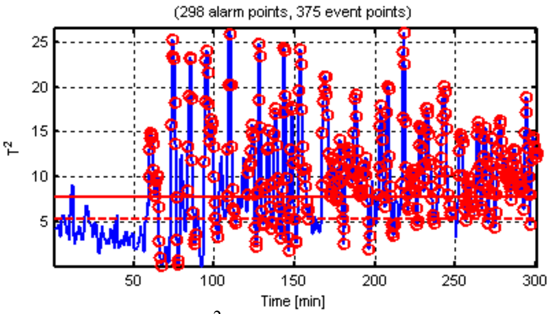

Figure 7: Hotelling's T^2 statistic (event logged after three consecutive alarms)

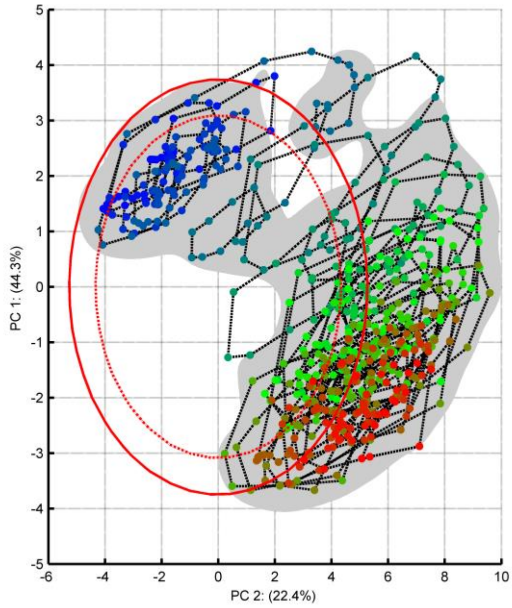

Figure 6: Mill state density (variance explained per PC shown in brackets)

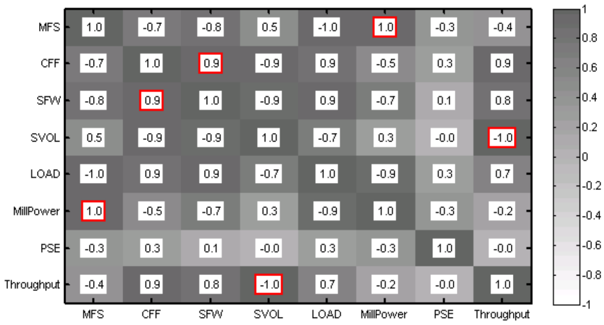

Figure 8: Fault data correlation plot

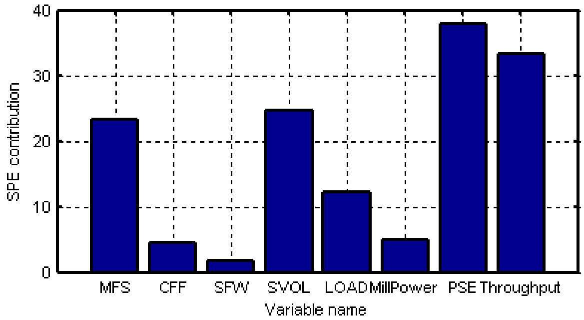

Figure 9: SPE contribution plot

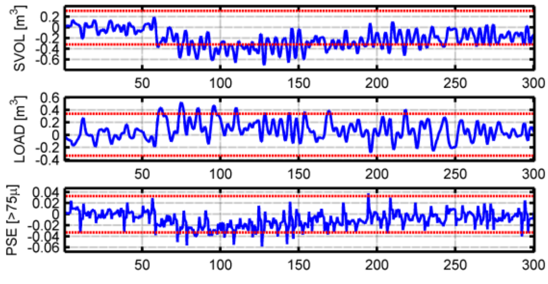

Figure 10: Controller set point tracking

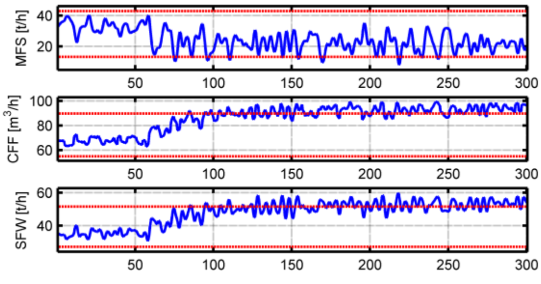

Figure 11: Controller manipulated variable use

indicate a compensating effect around the cyclone for less fines produced by the mill.

The contribution plot indicates that PSE, throughput, sump volume, MFS and mill load have the largest contributions to the SPE diagnostic statistic. Solid mill feed and mill load changes again reflect the change in grinding efficiency, while changes in product particle size, throughput and sump volume are symptoms of the ore hardness increase and associated decrease in grinding efficiency.

Controller set point tracking and manipulated variable use

Figure 10 confirms that the SVOL controller is not achieving set point, while the load and PSE controllers show less deviation, compared to training data (the limits shown).

Figure 11 shows that CFF has increased, again because the mill will be producing fewer fines for the same amount of power. One can also see that MFS has been decreased by the controller for the same reason.

6. CONCLUSIONS AND FUTURE DEVELOPMENTS

In conclusion, this paper has demonstrated that an insightful audit report can reveal how well, or otherwise, the milling process has behaved during a historical episode. Investigation of the mill state density plot and alarm events for SPC, SPE and T^2 supports the early detection of deviations and faults. One may gain significant insights into the milling operation from the correlation and controller plots, by understanding response to process disturbances in terms of pairwise interactions between variables and the behaviour of control variables under a given control strategy. This particular mix of statistics and mill control context, in conjunction with the proposed flow of interpretation, allows the reader of the audit report to learn from past experience; to gain insight into operational events and control strategy, beyond what can be learned from conventional KPI trends.

Potential future work includes improved SPC design, i.e. inclusion of rate-of-change limits. Furthermore, mill state clusters may be investigated by simulating a library of faults, so as further to aid the tracking of mill states and the diagnosis of potential fault causes.

7. REFERENCES

Aldrich, C.; Burchell, J.J.; Groenewald, J.W. de V. and Yzelle, C. (2014), Visualization of the controller states of an autogenous mill from time series data. *Minerals Engineering.* **56**. Pp. 1-9.

Coetzee, L.C. (2009), Robust nonlinear model predictive control of a closed run-of-mine ore milling circuit University of Pretoria PhD Thesis.

Coetzee, L.C.; Craig, I.K. and Kerrigan, E.C. (2010), Robust Nonlinear Model Predictive Control of a Run-of-Mine Ore Milling Circuit, *IEEE Transactions on control systems technology* **18(1).**

Craig, I.K.; Hulbert, D.G.; Metzner, G. and Moult, S.P. (1992). Extended particle-size control of an industrial run-of-mine milling circuit. *Powder Technology*. **73(3)**. Pp. 203-210.

Craig, I.K. (2012), Grinding mill modeling and control: past, present and future, 31st Chinese Control Conference. - Hefei, China. Pp. 16-21.

Cuevas, A. and Cipriano, A. (2008). State and ore hardness estimation in semiautogenous grinding. *IFAC Proceedings*. **17(1).** Pp. 3310-3315.

Ko, Y-D, and Shang, H. (2011). SAG mill system diagnosis using multivariate process variable analysis. *Canadian Journal of Chemical Engineering*. **89**. Pp. 1492-1501.

Le Roux, J.D; Craig, I.K; Hulbert, D.G; Hinde, A.L. (2013), Analysis and validation of a run-of-mine ore grinding circuit model, *Minerals Engineering*. **43**. Pp.121-134.

Muller, B. and De Vaal, P.L. (2000), Development of a model predictive controller for a milling circuit, *Journal of the South African Institute of Mining and Metallurgy*, **Nov/Dec.** Pp. 449-453.

MacGregor, J.F. and Kourti, T. (1995). Statistical process control of multivariate processes. *Control Engineering Practice*, **3(3)**, Pp. 403-414.

MacGregor, J.F., Kourti, T.; Liu. J.; Bradley, J.; Dunn, K. and Yu, H. (2007). Multivariate methods for the analysis of data-bases, process monitoring, and control in the material processing industries. *IFAC Proceedings*. **12(1)**. Pp. 193-200.

Remes, A., Karesvuori, J., Pekkarinen, H., Jämsä-Jounela, S-L. (2006) Integrated approach to monitoring and control of mineral grinding Processes. *IFAC Proceedings*. **1(1)**. Pp. 124-129

Wei. D. and Craig, I.K. (2008). Grinding mill circuits – A survey of control and economic concerns. *International Journal of Mineral Processing*. **90(1-4)**, 56-66.