A Holistic Approach to Control and Optimization of an Industrial Run-of-Mine Ball Milling Circuit

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Abstract: Anglo Platinum's control schema for a Run-of-Mine (ROM) ball milling comminution circuit follows a layered approach that involves basic control (regulatory, interlock and sequence control), fuzzy logic rule-based and model predictive control. This allows for a robust approach to optimization. This paper reviews the above control schema for a ROM ball milling circuit and discusses the benefits that have been achieved from implementing optimization using Mode Predictive Control (MPC) to cater for a wide range of feed conditions.

Keywords: **Comminution, Run of Mine, Ball Milling, Model Predictive Control, Constraints, Control Layers.**

1. INTRODUCTION

Comminution remains the most cost intensive process on mineral processing plants stemming largely from the high consumption of energy and grinding media (Napier-Munn et. al. 1999, Wei and Craig, 2008). Anglo Platinum has more then 40 tumbling mills installed across its operations in various configurations with a total installed power in excess of 150 MW. The optimization of these comminution circuits is a central research and development area within Anglo Platinum with the aim of reducing the energy footprint and improving the efficiency of its mineral processing operations.

Different milling circuit configurations are employed across Anglo Platinum's various concentrator operations. Primary milling circuit configurations vary from crushed ball milling to Run-of-Mine (ROM) ball milling to fully autogeneous grinding circuits, while the secondary milling circuit configurations vary from open to closed circuit classification configurations, depending on the ore type. Some concentrators also have IsaMills installed in a tertiary (Mainstream Inert Grinding) application. The overall performance of the milling circuit (referred to as a milling process cell) is a function of the various items of equipment making up that process cell (referred to as a unit), and the performance of each unit (mill, discharge sump, classification screen or cyclone, etc.) within the process cell is also dependent on the performance of the other units. This interaction typically results in a highly interdependent and non-linear process.

Anglo Platinum has developed a systematic and robust mill control solution to cater for the interdependencies and non- linearities typical of these circuits. Anglo Platinum's milling control solution (control schema) follows a layered approach that includes basic control (interlocks, sequences and regulatory control) and supervisory (consisting of fuzzy logic rule-based) control, (also referred to as expert control). This layered control schema developed by Anglo Platinum's Control Department and currently implemented on 17 tumbling mills in the group, ensures a robust and holistic approach to process cell optimization.

A recent addition to the control schema is a model predictive control (MPC) algorithm that facilitates a more precise optimization capability. This control advancement has been implemented on one of the ROM primary milling circuits. Figure 1 is a process flow diagram of the circuit that indicates the arrangement of the various controlled, manipulated and measured disturbance variables used in the MPC controller.

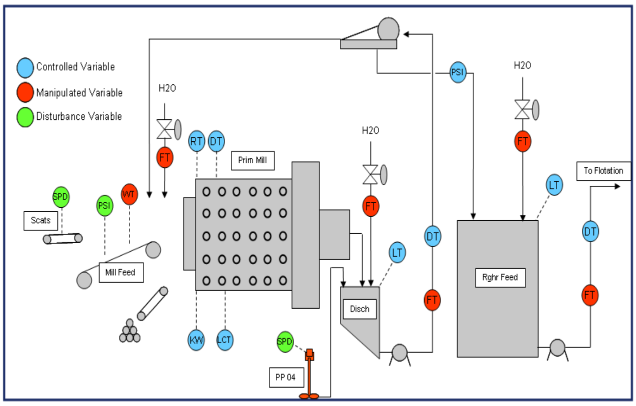

Figure 1: Process flow diagram of the primary ROM ball milling circuit.

This paper discusses the various control layers in the control schema developed for the above ROM ball milling circuit and focuses on the benefits that the supervisory layer with MPC optimization has introduced.

2. THE CONTROL SCHEMA

Anglo Platinum has a well developed supervisory control layer (APC layer) that is tightly integrated into the basic control schema. By combining the best-of-breed features found in various technologies, Anglo Platinum has derived an integrated APC product suite that provides all the tools required to design, deploy and support an ever growing APC footprint. The product suite is centered on a G2 based Expert System and is known as the Anglo Platinum Expert Toolkit (APET). Figure 2 shows the APET interface and control schema for the primary ROM ball mill discussed in more detail below. Figure 3 shows the APET interface and control schema for the primary ROM ball mill's discharge sump.

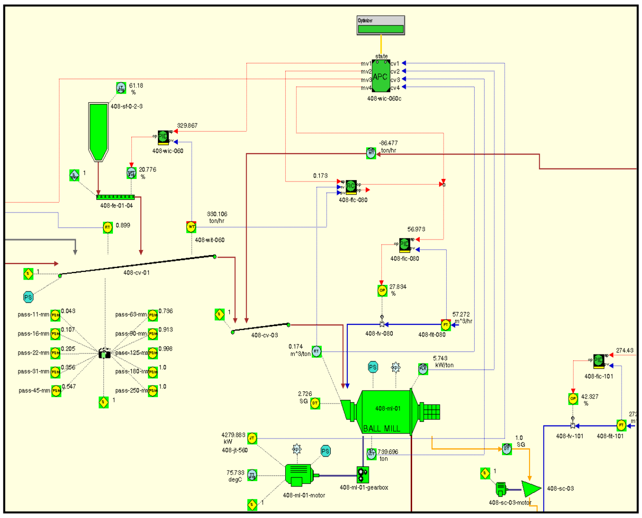

Figure 2: APET control schema for a primary ROM ball mill.

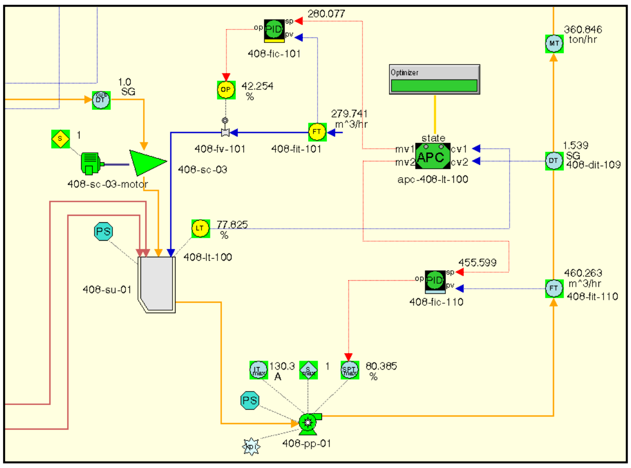

Figure 3: APET control schema for the primary ROM ball mill discharge sump circuit.

A standard interface module has been developed in the basic control layer that provides a single point of write access from APET to the PLC layer. This interface, in combination with the regulatory and interlocking schemes, ensures tight integration between the APC and the programmable logic controller (PLC) layer resulting in good overall system performance.

2.1. Basic Control Layer

The foundation layer of the control schema is housed in the PLC and consists of interlocks, sequences and regulatory type PID algorithms. The main objective of the basic control layer is to ensure a safe operation with adequate equipment protection while stabilizing important process variables such as the mill feed rate and mill inlet water flow rate. The basic control layer handles processing upset conditions, equipment failures and implements operator actions. This layer is a pre-requisite for the advanced process control (APC) layer. The basic control layer is implemented on a Siemens PLC using the Siemens PCS7 solution with tight integration into the WinCC Human Machine Interface (HMI) environment.

2.2. Supervisory Fuzzy Logic Rule-Based Control Layer

Fuzzy logic was invented in the 1950's as a way to translate linguistic statements into precise mathematical language by means of membership functions using terms such as high, low, increasing etc. (Johnston 1998). The Fuzzy-logic controller presents a highly robust solution (Johnston 1998) in an environment of non-linearity and interactive parameters, as is the case with most milling circuits (Muller and de Vaal 2000). The Anglo Platinum expert controller uses a combination of rules that include fuzzy memberships of mill power, mill load and feed to inlet water ratio. The fuzzy membership functions are described as the antecedents and occur mostly in a trapezoidal form as presented in Figure 4. From Figure 4 it is evident that the resulting belief of the various membership functions for a normalized load input of 0.6 is LOW = 0, OK = 0.25 and HIGH = 0.75.

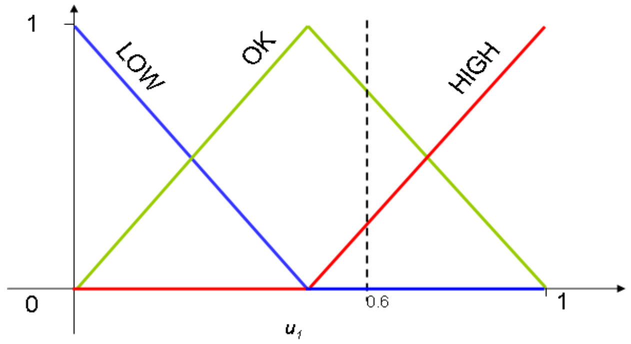

Figure 4: The fuzzy membership function of the normalized mill load (u on x-axis) with three membership functions (LOW, OK and HIGH).

These antecedents are applied to a rule set of the form IF – AND – THEN which results in the formulation of a degree of firing μ (Johnston 1998). A typical example is:

IF load high $A(x_i)$ **AND** load increasing $B(x_i)$ **THEN** decrease feed $D(\mu_i)$

Degree of firing is calculated as follows, note that ω_i presents a weighting applied to each term in the rule set, where μ for rule i is:

$$\mu_i = \varpi_{i,A} A(x_i) * \varpi_{i,B} B(x_i) \qquad (1)$$

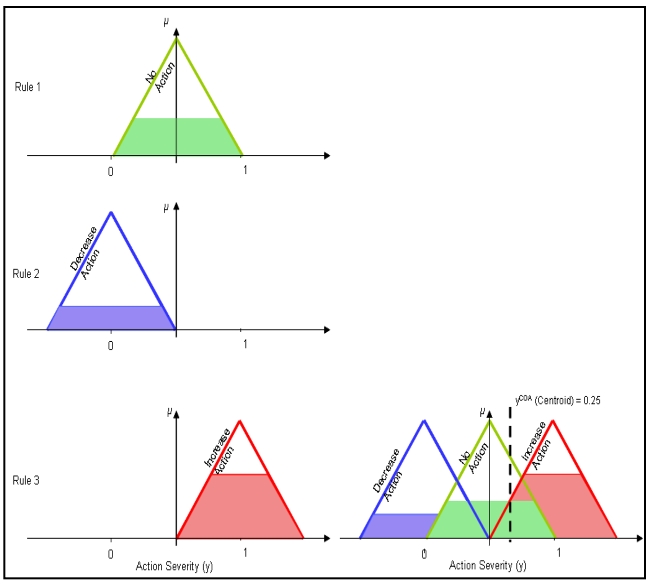

Figure 5: Combining the rules by means of the Centre of Area method

The next step in the algorithm is to combine all the rules by means of the Centre of Area (COA) method, graphically represented by Figure 5, as follows:

$$y_{COA} = \frac{\int y\mu dy}{\int \mu dy} \qquad (2)$$

The consequent or defuzzy membership function $F(y_i)$ then finalizes an absolute MV step S by making use of the resulting COA (y_{COA}) as shown in Figure 6.

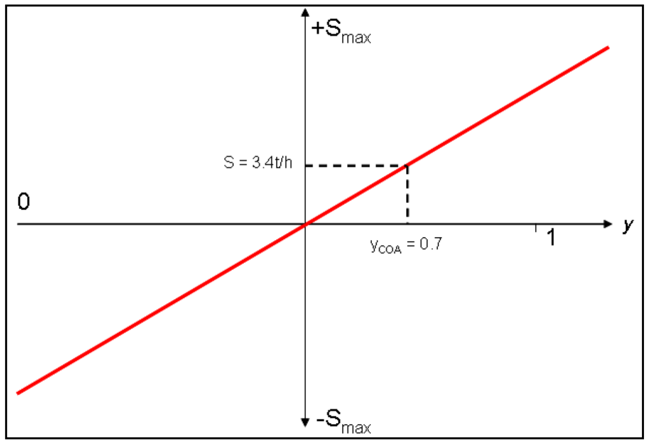

Figure 6: Defuzzyfication resulting in a positive mill feed step of S = 3.4tph.

The benefit of the controller was demonstrated through the stabilization of the mill parameters within a particular region on the power-to-load curve (defined by the control variable limits). The optimization objective of the controller is to approach the maximum power to load ratio of the curve, which Powell et. al. (2001), states to be the region where maximum transfer of energy to the charge occurs (and should result in the finest product grind).

2.3. Supervisory Model Predictive Control Layer

To further improve the control solution, a more mathematically precise optimization engine is required. Despite the non-linearity present in milling operation, economic and time constraints made it difficult to implement non-linear control and optimization. The fuzzy logic control infrastructure however made it possible to identify a linear region within which a linear controller could conduct this more precise optimization. The interfacing between the control algorithms are carried out seamlessly within the APET infrastructure.

Since the MPC is designed to operate in a limited range, a linear control formulation was chosen, namely Aspentech's DMCplus. The main advantages of MPC as described by Muller and de Vaal (2000) are:

i. The technique uses step response and not a transfer function or state-space model.

ii. Constraint handling or actuator and sensor failures are more easily dealt with.

This control engine is based on the Dynamic Matrix Control formulation first proposed by Cutler and Ramaker (1980), which has found widespread application in the refining and chemicals industries (Qin and Badgewell, 2003). The engine solves the following least squares optimisation problem to calculate moves in the manipulated variables:

$$\Delta MV = \left[A^T A\right]^{-1} A^T e \qquad (3)$$

The scope of the model predictive controller covers the mill, the discharge sump and the rougher feed tank. The design includes six manipulated variables (MVs), two feed forward variables (FFs) and eight controlled variables (CVs). Key MVs are the ore feed and dilution water, while the critical CVs are the mill load and power.

The linear dynamic models required for the controller were obtained by step-testing. This was performed in two phases; first a pre-step was conducted to obtain preliminary models, which were then used in an automated testing tool (Kalafatis et al, 2006) to obtain improved models. The resulting matrix contains thirty four models, thirteen of which are unstable or ramp models. A sub-set of the model matrix is shown in Figure 7. Of particular interest is the fact that the load models were found to be ramps, implying that the mill "pumps" material out at a rate that may be less dependent of load depending on the mill discharge grate and pulp lifter design.

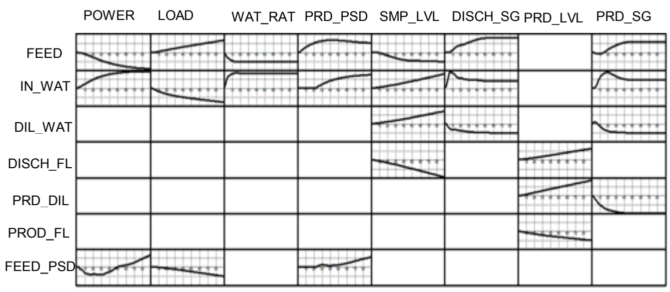

Figure 7: Subset of the dynamic model matrix

The control engine used can employ degrees of freedom to optimize the operation. The objective function can be formulated as a linear (LP) or quadratic program (QP). The LP formulation used is:

$$\min \phi = \sum_{i=1}^{NCOSTMV} \left(CST_i \times \Delta MV_i\right) + \sum_{j=1}^{NMOVEMV} \left(CST_j \times \left|\Delta MV_j\right|\right) \qquad (4)$$

In this case the LP was configured to minimize an objective, in the form of a milling efficiency function. Milling efficiency in this case was defined as the amount of power used to produce an amount of final product that is smaller than 75micron (kWh/ton -75µm).

$$J = \frac{Power}{Feed * x_{-75\mu m,p}} \qquad (5)$$

The coefficients in the LP (equation 4) were then found by considering the linear steady state model gains derived from the model matrix (Figure 7) and the milling efficiency. The resulting LP-coefficients indicated that maximising both ore feed and inlet water would lead to optimized milling efficiency.

3. RESULTS AND DISCUSSION

Figures 8 and 9 below are density plots for the mill power vs. load. The low density data (few data points) is represented by the grey and blue pixels and the high density data (large number of data points) by the yellow, orange and red pixels.

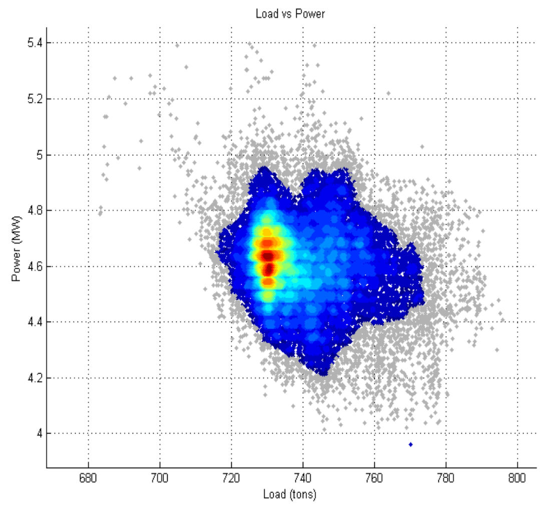

Figure 8: Power vs. Load density plot for periods with only fuzzy rules-based control active before MPC optimization.

Figure 8 represents power vs. load data with only the fuzzy rules-based controller active and Figure 9 data with the additional MPC optimization active. It is evident from Figure 8 that the power and load are primarily localized within a relatively small window that gets dictated by the controller CV limit selection.

From Figure 9 it is evident that when the MPC optimization is in control that there is an increased localization of power and load. This implies that both power and load can be controlled in a smaller CV limit range and therefore be shifted closer to the optimal region of maximum power to load ratio of the curve as described in section 2.2 (Powell et. al. (2001)) where maximum transfer of energy to the charge occurs that will result in the finest product grind.

Preliminary results indicate an increased stability of 15% for power and 25% for mill load and this is based on Anglo Platinum's developed stability index for such parameters.

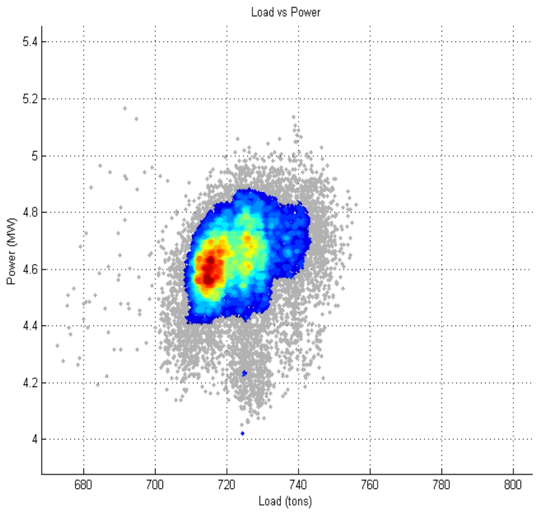

Figure 9: Power vs. Load density plot for periods with the MPC optimization in control.

4. FUTURE DEVELOPEMNT

Throughout the duration of the project, the availability of the online grind measurement was found to be lacking to be used as a raw input CV by the MPC controller. Anglo Platinum's Process Control Department decided to implement an inferential sensor based on selected historical data and continuously updated with quality assured current data to determine the resulting grind of the circuit. This sensor will be developed making use of non-linear modelling techniques such as Neural Networks supported by proven linear techniques such as Principle Component Analysis (PCA) frequently used by the Anglo Platinum Process Control Department in order to predict the grind from the main milling parameters. Establishing the quality of the prediction will also be necessary in the decision of allowing the sensor into closed loop control.

Once a reliable enough grind indication has been developed, the next phase of the project will be to include this grind as a CV and perform a study of the possible benefits that the MPC layer could deliver additionally by improving the mill grind.

5. NOMENCLATURE

A	Matrix of step response coefficients
CST_i	Cost factor for optimised MVs
CST_j	Cost factor for minimum move MVs
NCOSTMV	number of optimised MVs
NMOVEMV	number of minimum move MVs
e	CV error
ϕ	Objective function
ΔMV	Vector of calculated MV moves
$x_{-75\mu m,p}$	Fraction of particles in the product passing 75micron

6. REFERENCES

- **Cutler, C. R., & Ramaker, B. L., (1980).** Dynamic matrix control—a computer control algorithm. In *Proceedings of the joint automatic control conference*
- **Johnston, R., (1998),** Fuzzy logic for high performance control, *Applied Technology Laboratory, GEC-Marconi Materials Technology, Hirst Division*
- **Kalafatis, A., Patel, K., Harmse, M., & Zheng, Q., (2006).** Multivariable step testing for MPC projects reduces crude unit testing time, *Hydrocarbon Processing* **2**, 93-100
- **Muller, M. & de Vaal, P. L., (2000).** Development of a Model Predictive Controller for a Milling Circuit, *University of Pretoria.*
- **Napier-Munn, T. J., Morrell, S., Morrison, R. D., and Kojovic, T., (1999).** Mineral comminution circuits, their operation and optimization, *JKMRC – Queensland University*
- **Qin, S.J & Badgwell, T.A., (2003).** A survey of industrial model predictive control technology *Control Engineering Practice 11* 733–764
- **Wei, D. & Craig, I. K., (2009).** Economic performance assessment of two ROM ore milling circuit controllers, *Minerals Engineering.*