MODEL PREDICTIVE CONTROL OF SAG MILLS AND FLOTATION CIRCUITS

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ABSTRACT

Precise control of SAG mill loading and flotation cell level is critical to maximize production and recovery in mineral concentrators. While expert systems are commonly used to optimize these process operations, the underlying regulatory control is often implemented using traditional proportional-integral-derivative (PID) controllers or rule-based schemes in the expert systems themselves. This paper describes the use of a model-based predictive control (MPC) algorithm which has been proven to provide superior regulation for these processes. The controller is easy to apply due to its unique process modeling method based on Laguerre polynomials, with most applications installed in less than two weeks.

INTRODUCTION

Mineral recovery processes are notoriously difficult to control due to a combination of factors, including variable ore properties, complicated process dynamics, interacting process variables, and an inability to measure some key variables. However, as with all industrial processes, maintaining plant profitability requires that processes remain stable, production rates be held at optimal levels, yield (recovery) is kept high, product quality (grade) meets requirements, and energy and reagents are used effectively. A well-trained, experienced, and vigilant operator may be able to maintain process stability and keep production, recovery, and grade close to their targets; however, it is generally found that each operator tends to achieve these objectives with slightly different approaches to the operations, leading to some variability in the process between shifts. Additionally, even a great operator cannot hold the process at optimum conditions sustainably due to the minute-by-minute (or more frequent) adjustments that must be made to multiple variables. For these reasons, there is typically room to improve control of mineral recovery processes through the use of automation.

Considerable time and effort has been put into the development, installation, tuning, and testing of automation systems for mineral recovery plants. A typical simple approach is to use the traditional PID controllers, with traditional enhancements such as cascade control, feedforward control, ratio control, and so forth, that are available in plant distributed control systems (DCS). It is possible to have some degree of success in partially automating and bringing limited stability to processes with these techniques; however, PID does not perform well when there are challenging loop dynamics (such as the transport delay associated with ore feed systems, or the integrating behaviour of flotation cell levels), or multiple interacting variables (such as rotation speed and ore feed rate on SAG mill weight).

A more advanced approach to automation that seems to be popular among mineral processors is the use of rule-based expert systems. A number of these systems are commercially available and, typically, they take the form of software running on a PC that is frequently exchanging information (receiving process data and sending control outputs) with the DCS. The strength of these systems is that they provide an interface for codifying process operating procedures as a set of rules of control to be automatically followed. The idea is that these systems automate the practices of a best operator, so that these best rules are followed automatically and consistently at all times. Using expert systems, it is possible to have a high level of success in automating complex processes; however, there are limitations. Again, challenging loop dynamics or multiple interacting variables, can often cause poor performance, and when good performance is achieved, it requires complicated rule-based schemes. More generally, there is a drawback with the expert system approach in that a computer-based control system is able to control the process in a fundamentally different way than a human operator. In simply trying to automate the actions of even the best of human operators, there is the potential to miss an opportunity to make a full step improvement in the control of the process, by failing to properly leverage the speed, memory, and computational power and reliability available with computer-based control.
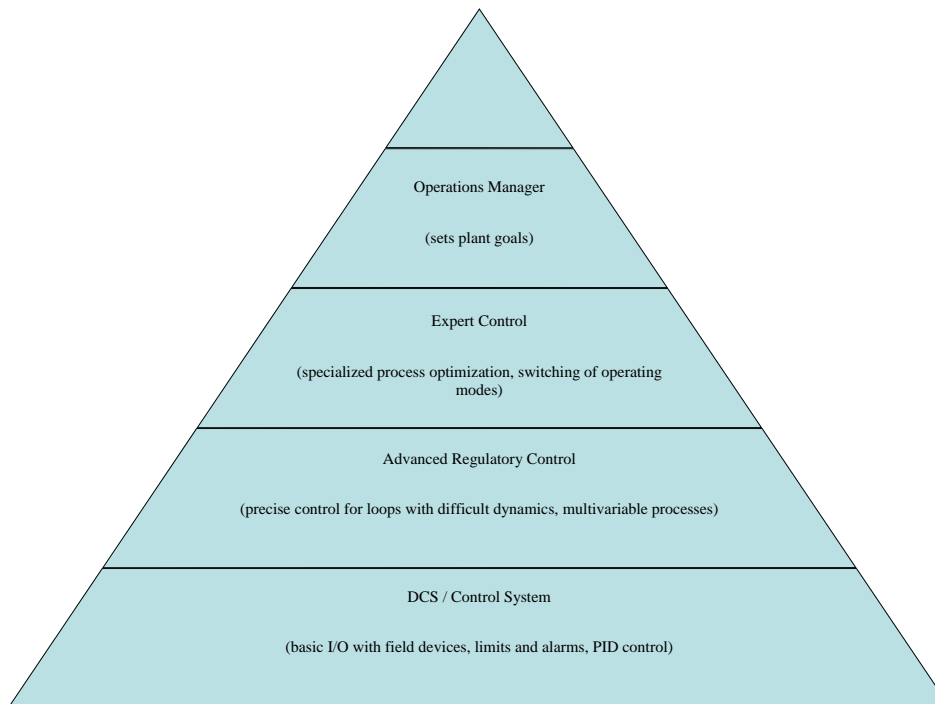
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Operations Manager

(sets plant goals)

Expert Control

(specialized process optimization, switching of operating modes)

Advanced Regulatory Control

(precise control for loops with difficult dynamics, multivariable processes)

DCS / Control System

(basic I/O with field devices, limits and alarms, PID control)

Figure 1 – Illustration of the comprehensive plant automation strategy

The paper advocates the use of MPC for mineral recovery processes. It is argued that MPC is able to provide a quality of regulatory control that cannot be matched by PID control or expert system control. The superior performance of MPC in controlling challenging loops provides a clear benefit in terms of plant profitability. Figure 1 shows a pyramid illustrating how advanced regulatory control is one of the foundational layers of a comprehensive plant automation strategy. It is suggested that it is not possible to complete this layer by trying to extend traditional DCS-based controls upwards, or expert system type controls downwards; so without the advanced regulatory control layer, the comprehensive plant automation strategy cannot be properly built.

In this paper, an industrially proven adaptive model-based predictive control strategy is reviewed and applications to SAG mills and flotation cells are presented.

ADAPTIVE MODEL-BASED PREDICTIVE CONTROLLER DEVELOPMENT

The advanced process control presented here is an adaptive model-based predictive controller that has its origins in the work of [1]. Zervos and Dumont proposed the use of a state-space model derived from the Laguerre orthogonal basis functions so that adaptive control could be achieved without the need to know the process order or the time delay in advance.

Laguerre basis functions may be defined by:

$$L_i(t) = \sqrt{2p}\,\frac{\exp(pt)}{(i-1)!}\,\frac{d^{i-1}}{dt^{i-1}}\left(t^{i-1}\exp(-2pt)\right) \tag{1}$$

Where L_i is the ith Laguerre function and p is a scaling parameter. Each Laguerre basis function is a polynomial multiplied by a decaying exponential and so these basis functions make an excellent choice for modeling transient behaviour because they are similar to transient signals. For use in modeling processes, these basis functions are written in the form of a dynamic system. With appropriate discretization (assuming straight lines between sampling points), the orthogonality of the basis functions is preserved in discrete time.

The state space model used by Zervos and Dumont takes the (velocity) form:

$$\Delta\mathbf{x}_{k+1} = \mathbf{A}\Delta\mathbf{x}_k + \mathbf{b}\Delta u_k \tag{2}$$
$$y_k = y_{k-1} + \mathbf{c}\Delta\mathbf{x}_k$$

Where u is the input variable, which is adjusted to control the process variable y. $\mathbf{x}$ is the nth-order Laguerre model state. The subscript k gives the time index in terms of number of controller update steps; so the operator Δ indicates the difference from the past update. For example, $\Delta\mathbf{x}_k = \mathbf{x}_k - \mathbf{x}_{k-1}$. The n×n matrix $\mathbf{A}$ and the n×1 matrix $\mathbf{b}$ have fixed values derived from the Laguerre basis functions. Values of the 1×n matrix $\mathbf{c}$ are adjusted during model adaptation to match the process model predictions to actual plant behaviour. The dimension n gives the number of Laguerre basis functions used in the process model. The algorithm presented here does not suffer with overparameterization of the process model and the BrainWave controller uses n=15, which has proven to be enough to model almost any industrial plant behaviour.

Notice that the state equation recursively updates the process state to include the newest value of the manipulated variable. Therefore, we can view the process state as an encoded history of the input values.

Model adaptation may be executed in real time following the recursive algorithm of [2]. This algorithm updates the matrix $\mathbf{c}$ according to:

$$\mathbf{c}_{k+1}^T = \mathbf{c}_k^T + \frac{\alpha\mathbf{P}_k\Delta\mathbf{x}_k}{1+\Delta\mathbf{x}_k^T\mathbf{P}_k\Delta\mathbf{x}_k}\left(\Delta y_k - \mathbf{c}_k\Delta\mathbf{x}_k\right) \tag{3}$$

Where the covariance matrix $\mathbf{P}$ evolves according to:

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$$\mathbf{P}_{k+1} = \frac{1}{\lambda}\mathbf{P}_k - \frac{\alpha\mathbf{P}_k\Delta\mathbf{x}_k\Delta\mathbf{x}_k^T\mathbf{P}_k}{1+\Delta\mathbf{x}_k^T\mathbf{P}_k\Delta\mathbf{x}_k} + \beta\mathbf{I} - \delta\mathbf{P}_k^2 \tag{4}$$

$\mathbf{I}$ is the identity matrix. The constants α, λ, β and δ are essentially tuning parameters that can be adjusted to improve the convergence of the adaptation.

The value of the input variable that will bring the process to set point (SP) d steps in the future may be calculated using the model equations. The formula for the process variable d steps in the future is:

$$y_{k+d} = y_k + \mathbf{c}\big(\mathbf{A}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{A}\Delta\mathbf{x}_k + \mathbf{c}\big(\mathbf{A}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{b}\Delta u_k \tag{5}$$

Since it is desired to have the process reach set point d steps in the future, we set $y_{k+d} = SP_{k+d}$ and solve for the control variable Δu_k.

$$\Delta u_k = \frac{SP_{k+d} - y_k - \mathbf{c}\big(\mathbf{A}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{A}\Delta\mathbf{x}_k}{\mathbf{c}\big(\mathbf{A}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{b}} \tag{6}$$

This equation is the basic control law. As with most predictive control strategies, implementation of the strategy involves calculating the current control output, implementing this new value, waiting one controller update period, and then repeating the calculation.

Predictive feedforward control can easily be included in this control formulation. A state equation in velocity form is created for the feedforward variable:

$$\Delta\mathbf{z}_{k+1} = \mathbf{A}_{ff}\Delta\mathbf{z}_k + \mathbf{b}_{ff}\Delta v_k \tag{7}$$

Where $\mathbf{z}$ is the feedforward state. The effect of the feedforward variable is then simply added to the output equation for the process variable:

$$y_k = y_{k-1} + \mathbf{c}\Delta\mathbf{x}_k + \mathbf{c}_{ff}\Delta\mathbf{z}_k \tag{8}$$

Notice that the feedforward state equation creates an encoded history of the feedforward variable in the same way that the main model state equation encodes the manipulated variable.

Re-deriving the control law from the extended set of process model equations yields:

$$\Delta u_k = \frac{SP_{k+d} - y_k - \mathbf{c}\big(\mathbf{A}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{A}\Delta\mathbf{x}_k - \mathbf{c}_{ff}\big(\mathbf{A}_{ff}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{A}_{ff}\Delta\mathbf{z}_k + \mathbf{c}_{ff}\big(\mathbf{A}_{ff}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{b}_{ff}\Delta v_k}{\mathbf{c}\big(\mathbf{A}^{d-1}+\mathrm{K}+\mathbf{I}\big)\mathbf{b}} \tag{9}$$

The basic structure of this control law does not change as additional feedforward variables are included in the process model, so it is a simply exercise to include as many feedforwards as necessary into this control law.

Use of the Laguerre process model implicitly assumes that a self-regulating process is to be modeled. In cases where a process exhibits integrating behaviour, such as SAG mills can exhibit at high loads, it is necessary to modify the Laguerre process model. The modification is two-fold. First, the

Laguerre model is altered so that the Laguerre state, gives the change in the slope of the process response. That is:

$$\Delta \mathbf{x}_{k+1} = \mathbf{A}\Delta \mathbf{x}_k + \mathbf{b}\Delta u_k \tag{10}$$

$$\Delta y_k = \Delta y_{k-1} + \mathbf{c}\Delta \mathbf{x}_k$$

$$y_k = y_{k-1} + \Delta y_k$$

Second, a disturbance component is added to the model. The feedback control law is then derived based on the modified Laguerre model, including the disturbance component.

The above gives the derivation of a d steps ahead adaptive model-based predictive control for a single variable. Full multivariable processes (multiple-input, multiple-output) may also be modeling using Laguerre state-space equations. However, to derive a control law for the multivariable case it is preferable to optimize for a cost function such as the one proposed in the generalized predictive control [3], rather than back calculating the control to achieve a d steps ahead outcome. Aside from this change in the derivation of the control law, the multivariable algorithm is substantially the same as the single variable algorithm. That is, a deterministic control law is obtained which provides the current control move that will yield some future process response, the current move is implemented, and then a new control move is calculated based on new process data at the next control update step.

The controller outlined above has demonstrated more than fifteen years of success in industrial applications, verifying the effectiveness of this adaptive model-based predictive control algorithm.

SAG MILLS

A semi-autogenous grinding (SAG) mill is a rotating cylinder containing steel balls that is used as an intermediate stage in the comminution (size reduction) of ore. Typically, these mills receive ore from a primary stockpile and, operating continuously, reduce the particles to a size appropriate for finer grinding in ball mills. As the name indicates, size reduction in a SAG mill occurs both from the tumbling action with the balls and from autogenous (rock on rock) grinding.

SAG mills are a critical component in mineral processing operations; at the same time, they are a difficult process to control. Due to this combination of factors, automatic control of SAG mills has received significant attention from mine operators and from advanced control system providers. One reason that SAG mill control is difficult is that there is a large number of variables governing the process, but only one main objective: maintaining (or maximizing) throughput. Many of the governing variables interact and it is not always clear how all of them affect throughput. Consider the variables included in the following basic description of SAG mill operations.

A number of feeders supply ore from the stockpile to a conveyor, which feeds the mill. As the ore is ground, water is added to assist in moving the particles through the mill. Depending on a number of factors, the weight of material resident in the mill will vary. It is important to maintain the weight within a specific range, as an overloaded mill quickly loses grinding efficiency, while an insufficiently loaded mill does not take proper advantage of the autogenous grinding mechanism. Grinding is also affected by rotation speed; in general, greater rotation speed allows for increased grinding. Finally, the power draw of the mill must be monitored to avoid exceeding the maximum power limit. Although brief, this description of mill operations begins to indicate the complex, multivariable nature of the SAG mill control problem. As is typical for challenging control problems, a number of different control strategies are proposed.

A very direct, and popular, approach to maximizing mill throughput is to gradually increase the feed rate to the mill until a high limit for weight or power draw has been reached. Should a high limit be violated, feed rate to the mill is reduced until mill operations return to acceptable limits. This approach has

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the advantage of being direct and easy to understand, but can result in a 'saw tooth' pattern of feed rate increases and decreases, which may not be desirable.

An alternative to this approach is to adjust mill feed rate to maintain mill weight at a set target. The idea justifying this approach is that there is a mill weight at which optimum grinding occurs. Therefore, by maintaining the correct mill weight, mill throughput is maximized. This approach has the benefit of increasing the stability of mill weight (and power draw). The drawback to this approach is that it is not always clear what weight target should be chosen, although adjusting the weight target to maximize power draw may complete this strategy.

Enhancements to these strategies may include the use of feed particle size distribution, ore hardness, and ore type as predictors for mill grinding efficiency. Mill sound may also be used as an indicator of the tumbling profile inside the mill. Some strategies have attempted to control the mill sound by adjusting mill rotation speed; however, this can be problematic due to the large and rapid effect that rotation speed can have on mill weight.

The adaptive model-based predictive control strategy outlined in this paper has been applied to a number of SAG mills in primary copper producing mines. The mills had a range of capacities, with the smaller mills operating at ore throughputs as low as 40,000 tons per day, and the larger mills operating at 120,000 tons per day or more.

The typical application of the adaptive model-based predictive controller for SAG mills is for control of the mill load. In these cases, mill load was inferred either from a direct weight measurement or from bearing oil pressure. Figure 2 gives a diagram showing the SAG Mill and the load control strategy. The diagram shows the fine ore feed belt bringing ore from the feeders under the stockpile to the SAG mill. The mass feed rate of ore is measured on the feed belt and typically an enhanced PID control strategy is used to control the ore feed rate. The PID controller gives a master feeder speed output which, typically, is then applied to each individual feeder with a different scaling so as to compensate for segregation of fine and course ore in the stockpile. The adaptive model-based predictive controller operates as a master controller over the feed rate controller. This controller takes the load measurement and set point, as well as key feedforward variables such as mill rotation speed, pebble recycle rate, and ore sizing information (coarse or fine fraction) and sets the set point for the feed rate controller. In some cases the adaptive MPC may also be used for the feed rate control itself. Where there is significant transport delay between an increase in the addition of ore to the feed belt and the measurement of that feed rate increase, MPC can provide improved feed rate control.
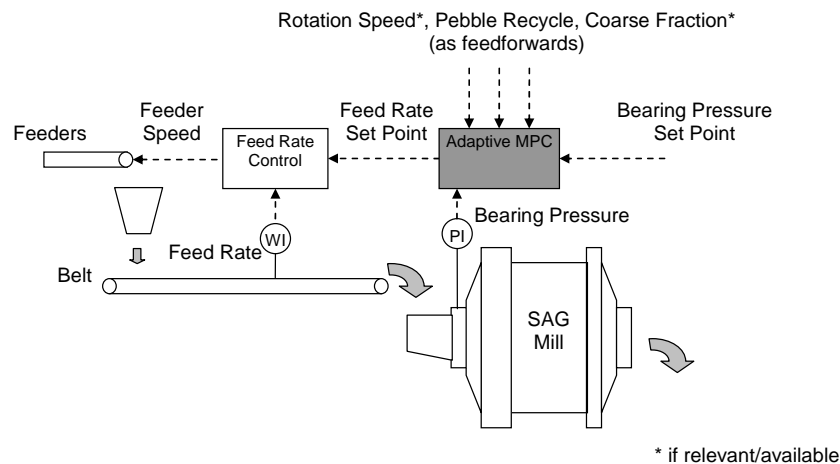

Figure 2 – The adaptive MPC applied to SAG mill load control

It should be noted that in the majority of cases, this MPC strategy was implemented on SAG mills that were already operating with expert system control. This MPC strategy was integrated with the expert system, taking over the task of setting the feed rate to the mill.

Results from the implementation of the adaptive model predictive control strategy were in the range of a 1.5 to 2% increase in ore throughput relative to mill throughput with expert system control alone. Table 1 lists some results. To emphasize the significance of these increases, note that for a concentrator processing 120,000 tonnes per day of ore at a grade of 0.75%, with a recovery of 0.85, total annual copper production is roughly 550 million pounds. Even at a low profit margin of $0.20/pound, a production increase of 1% is worth over one million dollars per year.

Table 1 – SAG Mill Throughput Increases with MPC

Mine Site	Number of SAG Mills	Production Increase
Minera Candelaria	2	1.6%
Minera Escondida – Laguna Seca	1	>2%
Minera Los Pelambres	2	1.5%

Figure 3 displays some process data from one of the applications. These trends some the MPC controller at work over a period of several days. The trend also shows that when the MPC was taken off-line for some hours for maintenance the expert system was not able to maintain the mill load with the same stability. This particular concentrator plant is fed with a mixture of two ore types with significantly different work indexes. For this reason, grinding rates in the mill appear to change frequently and rapidly and the MPC control proved to react sooner and better minimize the disturbances caused by these events. The impact of using MPC on overall mill performance was shown to go far beyond stabilization of mill load. One plant site observed reductions well above 50% in the standard deviations of ore feed rate, mill rotation speed, mill weight, and mill power draw.

FLOTATION CELLS

Mineral flotation is a process that takes advantage of differences in hydrophobicity to separate valuable minerals from gangue or one valuable mineral from a bulk concentrate. Hydrophobic ore particles become attached to air bubbles which rise to the top of the flotation cell to form a froth layer. The froth is collected as it overflows the top of the cell while the rest of the material passes through the cell outlet. Typically, a number of cells are arranged is series so that as the pulp flows through a flotation line, the hydrophobic particles have a number of opportunities to separate from the pulp. The success of the flotation process is measured by how well one component is selectively removed from the bulk feed. For example in copper flotation, the valuable product, copper, is floated to separate it from the gangue. Both the recovery (fraction of the total copper available that reports to the froth) and the grade (purity of the froth) are important.

To promote the success of flotation, it is important to have good control of the froth depth. Commonly froth depth is inferred by measuring the location of the froth-pulp interface (with a float device) relative to the lip of the cell. Under normal cell operations, froth will completely fill this space, from the top of the liquid level in the cell up to the lip of the cell. If the froth level can be maintained, a stable froth layer is formed without excessive bubble breakage, and there is a steady overflow of froth over the lip of the flotation cells. A well-chosen froth depth allows time for some 'drainage' of entrained water and gangue particles before the froth overflows the cell [4]; however, greater froth depths can result in lower recovery and increased use of expensive frother chemicals.
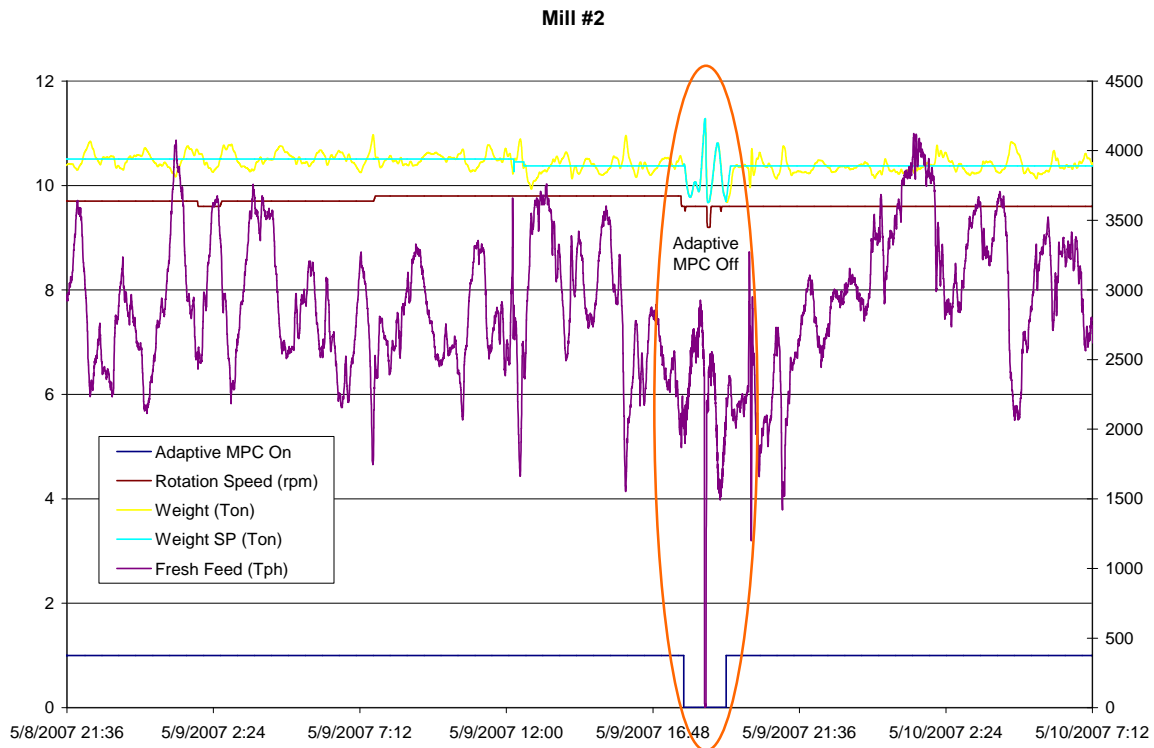
Mill #2

Figure 3 – Trends showing model-based predictive control of a SAG mill. The portion of data which is circled shows the less stable behaviour of the mill while under expert system control only

Froth level control can be a challenging problem for a number of reasons. There can be large and sudden changes in the flow of pulp into the flotation line. Often this flow is unmeasured and the changes can cause large level disturbances. The arrangement of a number of flotation cells in series means that the outlet flow from one cell is the inlet flow to the next cell in the line. Therefore, as outlet valve position is adjusted to control cell level, the levels in downstream cells will be affected. The valves used in flotation applications are often dart valves or pinch valves that may not always have a fast and accurate positioning response. To summarize, control of flotation level is difficult due to the combination of significant unmeasured process disturbances, interacting process variables and imperfect actuators.

Adaptive model-based predictive controllers, as described above, were applied to two copper rougher-scavenger flotation lines, each consisting of five 160 m³ flotation cells. Each cell level is controlled by an individual controller which adjusts the cell's outlet valve position. To compensate for the impact of valve position changes on downstream cell levels each level controller takes the upstream cell's outlet valve position as a feedforward. This allows each controller to minimize disturbances by adjusting outlet valve positions at the same time as the inlet valve positions are changing. Figure 4 provides a simple diagram illustrating the application of the control loops.
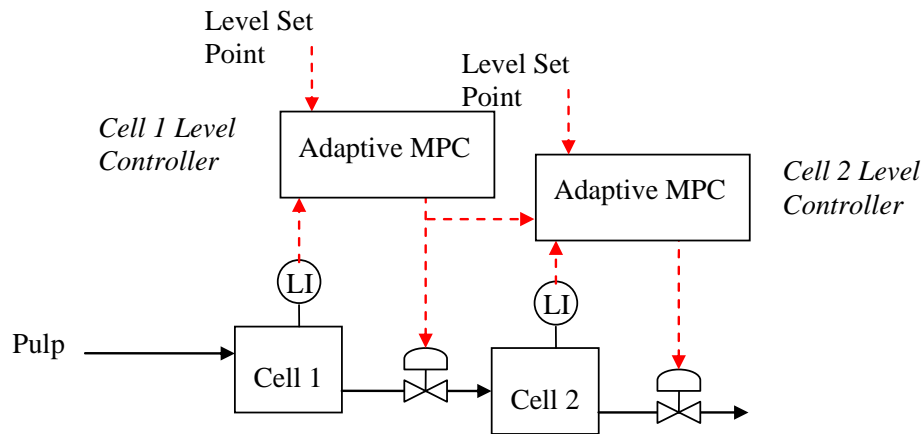
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Figure 4 – Diagram showing the control loops used for flotation level control

The advanced control loops replaced PID loops upon which the plant had previously relied to maintain cell level. The PID controllers had struggled to maintain tight control and had particular difficulty stabilizing the cells after large disturbances or on plant start-ups. Figure * demonstrates the improvement to the cell level control that was achieved from replacing traditional PID loops with the more advanced loop controllers. In this case there was a 60% reduction in level variability as measured by standard deviation. More generally, there was a typical improvement of over 50%.

It is suggested that improved level stability has the effect of improving mineral recovery, improving product grade, and the reducing frother consumption. However, these are difficult benefits to prove, due to the problem in obtaining and collecting sufficient data, where the comparisons can be made given the same operating conditions (for example, with the same production rates and ore types). Unfortunately, to date, plant staff have not been able to complete such an analysis. However, one obvious and easily measurable benefit came from the improved control performance on large production rate changes or plant start-ups. It was observed that the PID controllers had difficulty in stabilizing the cells after these events; often cell levels could swing wildly for as much as two hours before settling into what could be considered steady-state. This settling time was greatly reduced with once the advanced controllers replaced the PID loops. The benefits from avoiding this loss in operating time can be calculated. An example calculation can be made based on the example business fundamentals given in Table 2.

Table 2 – Example Mineral Concentrator Business Fundamentals

Tonnes Milled per Day	50,000
Copper Grade	0.3%
Recovery	75%
Tonnes Copper Produced	112.5
Pounds per Metric Tonne	2,205
Price per Pound	$2.00
Production Cost	$1.50
Daily Revenue	$124,031

If the adaptive model-based predictive control reaches 'steady state' in one hour less than PID control, and there is one of these large disturbances events per week, then this represents the equivalent of 2.2 more days of operating time per year. Based on a daily revenue of $124,031, this gives a benefit of $272,869 annually. In the actual application, the benefit from this sort of calculation was estimated as $562,755.

Note that this is only the 'easily' calculated benefit and does not include the additional benefits to be obtained through improvements in recovery. Examining the simple calculation of daily revenue made in Table 1, shows a sensitivity of $1654 per day per percent recovery. Therefore, even a modest 0.5 percentage point increase in recovery from improved froth level control yields close to $300,000 per year in additional profit.
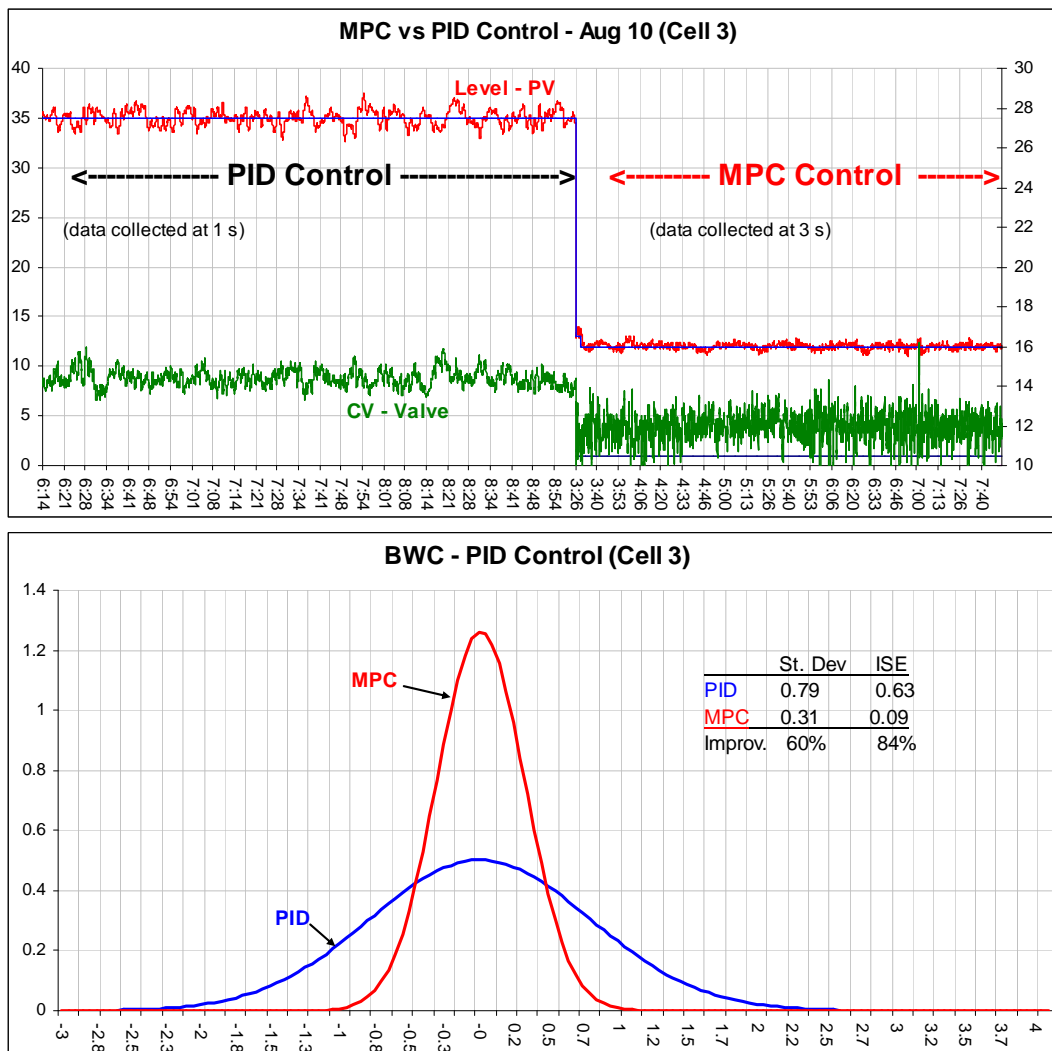

Figure 5 – Comparison of PID control and MPC for flotation level control

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CONCLUSIONS

An industry-proven adaptive model-based predictive control algorithm has been examined. The algorithm has been applied to yield performance improvements to SAG mill load control and to froth flotation level control. MPC was used to stabilize the weight or bearing pressure for SAG mills leading to demonstrated throughput increases greater than 1.5% at three separate mine sites. These performance improvements are relative to the expert systems already in use at these sites. One mine site reported secondary benefits of over 50% variability reductions in mill noise, rotation speed, feed rate, and power draw. For flotation, cell level variability was shown to be reduced by 50% when using MPC instead of PID control. Additional stabilization time after large production rate changes was reduced by 1 hour.

ACKNOWLEDGEMENTS

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