SAG MILL OPTIMIZATION USING MODEL PREDICTIVE CONTROL

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ABSTRACT

Semi-Autogenous Grinding mills can be optimized for maximum ore throughput or maximum grinding energy efficiency. In both cases, precise control of the mill weight is critical. Model predictive control provides an additional tool to improve the control of Semi-Autogenous Grinding mills and is often able to reduce process variability beyond the best performance that can be obtained with proportional-integral-derivative or expert system control methods. Model predictive control is able to optimize the control of processes that exhibit an integrating type response in combination with transport delays or variable interaction, which are characteristic of the Semi-Autogenous Grinding mill weight control problem.

KEYWORDS

SAG mill, model predictive control, MPC, expert systems, optimization, Laguerre

INTRODUCTION

Mineral processing operations present many challenges for automatic process control due to variations in unmeasured ore properties, material transport delays, and nonlinear response characteristics. Control of Semi-Autogenous Grinding (SAG) mill weight is an example of an important process that exhibits many of these aspects. Maintaining the SAG mill weight at the optimum value is critical for achieving maximum grind rate efficiency and mill production (Powell, M.S., van der Westhuizen, A.P., & Mainza, A.N. 2009). However, SAG mill weight is difficult to control as the dynamic response changes as the mill approaches maximum capacity. Near maximum capacity, the weight response exhibits integrating behavior, and the mill can overload quickly. This situation is complicated by the transport delays in the feed system, so it is important that the control system can detect the imminent overload and adjust the feed rate quickly to prevent an overload.

Expert systems are a popular approach to manage the control of these difficult processes in the mining industry. In some cases, the expert system may control the actuators directly using a rule-based approach, or rely on conventional proportional-integral-derivative (PID) loop controllers to perform the underlying regulatory control of the process where possible.

For SAG mill control, expert systems are often used as they are able to detect the rapid increase in mill weight and anticipate an imminent overload using combinations of rules. However they often reduce the feed rate more than necessary in some situations, and require time to return the feed rate to maximum levels, which decreases production capacity. Developing the expert system rules to manage the dynamic response of a process is not a simple task. The rules must manage error from the target as well as the rate of change of the process. If measured disturbance variables such as pebble recycle, ore feed size distribution or mill rotation speed are also included in the control design, then the expert rules become even more complex. Adjusting these rules to obtain optimal control response under all situations is difficult because there is no theoretical basis for determining these settings. This leads to a trial and error approach with uncertain dynamic control performance results. At some point, managing the control of a process with an increasing number of rules is not practical.

Model Predictive Control (MPC) provides an additional tool to improve the control of critical processes where PID or rule-based expert control is not well suited to the application. MPC is often able to reduce process variability beyond the best performance that could be obtained with PID or expert system control methods. MPC is able to manage applications where there are delays in the process response to actuator changes or multiple interactions between process variables. In particular, MPC is able to optimize the control of processes that exhibit an integrating type response in combination with transport delays or variable interaction. This type of response is particularly difficult to control, and it is common in mineral processing for many different processes including level control of flotation cells and crushers, and SAG mill weight control.

The application of MPC control is guided by an established theoretical basis. Unlike the rulebased control approach of expert systems, MPC performance can be predicted and optimized in a systematic manner that ensures the dynamic control results are as expected. This enables MPC to be applied efficiently with less trial and error compared to rule-based controls.

MPC has been successfully applied to SAG mill control at several copper mines in South America. In each case, MPC was used to enhance or replace elements of the existing advanced control system. MPC consistently demonstrated the ability to provide reduced process variability and increased stability compared to PID or expert system based control.

MODEL PREDICTIVE CONTROL DESIGN

Obtaining a process response model is a key part of the implementation of an MPC controller. In our design, the controller models the system response using a generic function series approximation technique based on Laguerre polynomials. This approach provides a simple and efficient method to mathematically model the process response with a minimum of a priori information. It also enables the controller to perform online adaptation of the process response models automatically, which is not possible when using models based on a simple open loop time series. The adaptive capabilities assist the control technician with developing the process response models, and the default configuration of the control parameters ensures excellent control performance once the process model is obtained. These factors reduce the implementation effort and contribute to quick installation times. For industrial customers that operate large plants with thousands of process controllers, this one benefit of MPC is extremely valuable.

Using these models as the basis for a predictive control design, the MPC is able to control processes with long delay or response times better than is possible using PID type controllers. This technique can also be used to automatically model and counteract the effects of measured disturbances by incorporating them into the control strategy as feed forward variables. The use of feed forward variables is particularly important for long time delay systems so that disturbances can be cancelled much sooner than is possible using feedback control alone.

The design of the model predictive controller presented here has its origins at the University of British Columbia (Zervos & Dumont, 1988). They proposed the use of a state-space model derived from Laguerre orthogonal basis functions so that process response model identification and adaptive control could be achieved without the need to know the process order or the time delay in advance. An analogy to this method is the use of Cosine functions in the Fourier series method to approximate periodic signals as is common in frequency analyzers. In this case, weights for each Cosine function in the series are determined such that when the weighted Cosine functions are summed, a reasonable approximation of the original signal is obtained. In this case, the signal is represented by its frequency spectrum, with each basis function weighting coefficient representing the contribution of each frequency present in the original signal. This method is efficient due to the similarity of the basis functions in the series to the signal being modeled, and also due to the special mathematical property of the basis functions called orthogonality that ensures a unique solution of the basis function weighting coefficients in the identified model.

In process control, the process transfer functions are transient in nature and are not periodic, so Cosine functions are not an appropriate choice as a basis for the model structure. However, the elegance of the Fourier series technique provides many advantages such as simple and efficient model structure and excellent parameter convergence when estimating the model from observed data sets due to the orthogonality property of the Fourier series. The motivation of this research was to find an equally simple and efficient method to model the transient responses common in process control applications.

The Laguerre functions are well suited to modeling the types of transient signals found in process control because they have similar behavior to the processes being modeled and are also an orthogonal function set. In addition, the Laguerre functions are able to efficiently model the dead time in the process response compared to other suitable function sets. The Laguerre model is used as a basis for the design of the predictive adaptive regulatory controller.

After the process response model is obtained, a predictive control design is used to calculate the actual output actions of the controller. Generalized predictive control (Clarke, Mohtadi, & Tuffs, 1987) is one method that involves minimizing an objective (cost) function J(*) of the predicted set point tracking error and future actuator movements to determine the best set of control moves as shown in equation (1).

$$J(\Delta u) = \sum_{i=N_1}^{N_2} ||\hat{Y}(i) - \hat{S}(i)||_Q^2 + \sum_{i=1}^{N_u} ||\Delta U(i)||_R^2$$
(1)

This concept of predictive control involves the repeated optimization of a performance objective over a finite horizon extending from a future time (NI) up to a prediction horizon (N2). Figure 1 characterizes the way prediction is used in the MPC control strategy. Given a set point s(k + l), a reference r(k + l) is produced by pre-filtering and is used in the optimization of the MPC cost function. Manipulating the control variable u(k + l) over the control horizon (Nu), the algorithm drives the predicted output y(k + l) over the prediction horizon, towards the reference.

The control moves are determined by looking at the predicted future error, which is the difference between the predicted future output and the desired future output (reference). The user can specify the region over which these error values will be summed. The region is bounded by the initial (N1) and final (N2) prediction horizon. It is also possible to set the number of control moves that the controller will take to get to the set point by adjusting a parameter called control horizon (Nu). The predicted squared error from set point and the total actuator movements are weighted with matrices Q and R respectively to form the objective (cost) function J(*).



Figure 1 – MPC concept

Solving the optimization is typically done using search-based methods. These methods have the disadvantage of unpredictable convergence time so it is difficult to assure that a control update is ready at the next required execution interval of the controller. There is also the problem of finding solutions that are local minimums and not global minimums in the allotted search time, so the control results may not be optimal.

An alternative method to solve the minimization of the objective function involves deriving a deterministic control design that uses a least squares approach instead of a search-based method. Input constraints are implemented via a multivariable anti-windup scheme, which was proved to be equivalent to an online optimization for common processes (Goodwin & Sin, 1984).

This deterministic control law 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. For a complete mathematical development of the control law used in the multivariable case, refer to Huzmezan (1998).

For applications of the MPC that involve just a single control output, a deterministic control law can also be obtained using a simple d-steps ahead process response prediction with a single step control horizon. In this case, the complexity of the design is greatly simplified and the control output can be calculated directly without the use of a search-based optimizer or a least squares calculation. For a complete mathematical development of the control law used in the single variable case with a Laguerre state space model, refer to Zervos and Dumont (1988).

The Laguerre function-based MPC controller outlined above has demonstrated more than 20 years of success in industrial applications, verifying the effectiveness of this adaptive model-based predictive control design.

MODEL PREDICTIVE CONTROLLER IMPLEMENTATION

Despite the complex mathematics used in the control and model adaptation algorithms, the MPC is implemented as software that is designed to be easy to use and suitable for control technicians to apply in an industrial setting. The system connects to existing control systems using the OLE for Process Control (OPC) standard interface. A communications watchdog scheme is used to ensure that the process control automatically reverts to the existing control system in the event of any communication or hardware faults associated with the MPC computer.

The user interface for the MPC software is shown in Figure 2. The interface includes a trend display of the process variables at the top right side of the interface. In this example, the set point is the yellow line, the process variable is the red line, and the controller output (the actuator) is the green line.

The identified process transfer function is shown on the lower right side. The transfer function plot is generated based on a step input at time = 0 and thus shows the open loop transient response of the process to a change in the actuator or measured disturbance variable. The white line is a plot of the estimated transfer function of the process (expressed as a simple first order system using a dead time, time constant, and gain), which is used as a starting point for the model identification. The red line is a plot of the identified process transfer function open loop step response based on the Laguerre representation. The blue bars represent the relative values of the 15 Laguerre series coefficients that are the identified process model parameters.

BrainWave - User Interface (Revision 8.03)				_ 8 ×
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BWC Control Panel	Trender for Loop 3			
Loop #3- Under Damped Second Order	C Real Time	PV= 50.07	SP= 49.96	CV= 29.95
PV Description 49.96	View			-80
CV Description 29.96				60
FF1 Description 20.00	Pen Setup PV FF1			40
FF2 Description 0.00	SP FF2 CV FF3			
FF3 Description 0.00				10:42:32:3
All Loop	10:39:12:8	10:39:52:8 10:40:32	:8 10:41:12:8	10:41:52:8 10:42:32:8
«« »» 3 MAII PLC BWC	Mode: Historical	Sample: 4000	Sample I	nterval: 0.50 (s)
Model Learning	Model Viewer for Loop 3 (Act	ive Scenario : 0)		
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Figure 2 – MPC software user interface

MODEL PREDICTIVE CONTROL OF SAG WEIGHT

The MPC controller was installed to control the SAG mill weight, the belt weight in the ore feed system, and the SAG mill sound emissions. A diagram of the control strategy is shown in Figure 3.



Figure 3 – SAG mill MPC control strategy

The MPC SAG weight controller includes measured disturbance variables such as pebble recycle and ore size distribution as feed forward inputs to improve control of the SAG mill weight when changes to these variables occur. The MPC control is able to maintain mill weight on target with less variability and avoid overloads without making excessive reductions to the ore feed rate. This performance improvement enables the mill to operate closer to optimum grinding conditions. As shown in Table 1, in each case the improved control with MPC demonstrated an average increase in mill production of 1.6% or more on several SAG mills at copper mines in South America.

Mine Site	Number of SAG Mills	Production Increase
Minera Candelaria	2	1.6%
Minera Escondida – Laguna Seca	1	>2%
Minera Los Pelambres	3	1.64%

Table 1 – SAG mill production increases with MPC

A comparison of the SAG mill weight control performance at Minera Los Pelambres for MPC and expert system control over a period of five months is shown in Table 2. Despite a lower average percentage of fines in the ore feed, the MPC control provided a production increase of 1.64% compared to expert control. The standard deviation of the production rate was reduced by almost 55% with MPC, which contributes to increased stability of the downstream processes in the Ball Mill and Flotation circuits. The standard deviation of the mill weight was reduced by almost 84% with MPC, even though the standard deviation of the feed ore size was 2.7% higher for the MPC control periods. This reduction in mill weight variability allows the mill to operate closer to the optimum target fill weight, resulting in increased grinding efficiency and higher production capacity.

on Rate Mill Weight	% Fines
3913.2	32.7
105.6	12.1
3947.2	33.6
655.6	9.8
.64%) -34.0 (-0.86%) -0.9 (-2.7%)
4.6%) -550.0 (-83.9%) 2.3 (+23.5%)
	m Rate Mill Weight 3913.2 105.6 105.6 3947.2 655.6 64%) -34.0 (-0.86%) -34.0 (-0.86%)

Table 2 – SAG mill performance comparison – MPC vs. expert system control

A time series chart of the SAG mill weight control performance is shown in Figure 4. The maximum feed rate of fresh ore is set by the operator based on plant operating constraints. When the MPC is limited by the specified maximum feed rate, the SAG mill weight does not achieve the set point and the feed rate is constant at the operator limit as indicated on the chart. As ore properties change, the SAG mill weight starts to approach/exceed the set point and the MPC controller adjusts the feed rate as required to prevent overloads and maintain the weight on the target. The control response of the MPC is very dynamic during these periods. This control response would be difficult to produce using expert system rule-based methods, which highlights the basis for the performance improvement achieved with MPC.



Figure 4 – SAG mill MPC control chart

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