INDUSTRIAL RESULTS USING MODEL-BASED EXPERT SYSTEM CONTROL OF MINERAL PROCESSING PLANTS

A.E. Oblad (1) and J.A. Herbst (2)

RESUMO
O desenvolvimento de modelos matemáticos das operações de britagem, moagem e flotação possibilita o projeto de sistemas de controle que possuem a capacidade de melhorar significativamente a performance de usinas minerais em relação ao controle automático convencional. Os sistemas avançados de controle contêm modelos dinâmicos para avaliar os efeitos de ações controladoras, estimadores ótimos para obter os valores de variáveis não mensuráveis (especialmente características do minério), estratégias otimizantes de controle que aumentam a performance da usina, e "Expert Systems" que implementam a estratégia. O presente trabalho reporta sobre umas aplicações de controle baseado-em-modelos. Estas incluem usinas de moagem semiautogêna (SAG), moagem convencional (moinhos de barras e bolas), e flotação. O método resultou em aumentos de capacidade de 5% a 15%. Quatro aplicações industriais são apresentadas que demonstram a eficácia de controle baseado-em-modelos.

ABSTRACT
With the development of accurate dynamic models of crushing, grinding and flotation it has been possible to design control systems which result in improved plant performance in comparison with manual or conventional control. These advanced control systems consist of dynamic models for evaluation of control actions, optimal estimators for obtaining values of unmeasurable variables (especially ore characteristics), optimizing control strategies that increase overall plant performance, and Expert Systems which implement the control strategy. This paper reports on applications of model-based control to SAG, ball/rod mill, and flotation plants. This approach has resulted in plant capacity increases of 5% to 15%. Four case studies are presented which demonstrate the effectiveness of model-based control.

(1) Metallurgical Engineer, Senior Systems Engineer, Control International Inc., Salt Lake City, Utah, USA
(2) Metallurgical Engineer, President, Control International Inc., Salt Lake City, Utah, USA
Model based control strategies have the potential to become an essential feature of automatic control systems for mineral processing operations. Before 1980 distributed control systems provided by major vendors were usually based on minicomputers. With the introduction of more powerful microcomputers and control software designed for them, the personal computer has become a viable alternative to minicomputers. A typical control microcomputer runs at 20 MHz with 4-8 MB of memory. A high speed serial network transfers data to the plant at a typical rate of 38400 baud. Just as microprocessor based controllers have enabled the use of adaptive and auto-tuning proportional-integral (PI) control loops, so too will distributed control systems play an important role in implementing model based control strategies.

Models can be used in various ways in a control strategy. When the objective is to minimize the variance of the outputs of a process, then dynamic models of the process can be used to find the optimal inputs. When the objective is to find the operating conditions that maximize profit or minimize cost, then from steady state models the desired level of process outputs is found. In both cases it is up to the control system to ensure that the setpoints provided by the model are achieved; the models act as a supervisor for the control system. The model when combined with an extended Kalman filter can be used to estimate variables too costly or difficult to measure. The Kalman filter estimates of measurements contain less random error, thus improving the accuracy of calculations made with such measurements or even replacing a measurement when an instrument fails.

MODEL BASED CONTROL

Many of the limitations in classical control strategies are due to a lack of information about the magnitude of controlled variable responses to manipulated variable changes and the nature of the interactions between
variables (Herbst and Rajamani, 1982). The problem is further aggravated by the fact that important disturbances, such as mineralogical composition and hardness changes cannot be directly measured at the present time. Feedback control methods assume that the direction of change in a manipulated variable for corrective action in a control variable is known and that controller gains can be found which are suitable for all circumstances. But often the mineral processing system responses are too complicated to be characterized by such simple descriptors. An obvious solution to such a problem is to build a model, which contains the missing information about the process, into the strategy. By building in such a model, "well informed" responses to disturbances can be made and, ultimately, truly "optimal" control performance can be achieved.

The nature of a model based control strategy is revealed in Figure 1. The essential features are 1) a process model which is simple enough to be used for rapid on-line calculations but detailed enough to faithfully reproduce the essential dynamic characteristics of the process, 2) an estimator which combines measurements within the process and model information to determine the state of the system at any instant in time and 3) an optimizer which uses the current state of the system and the model to select the path for manipulated variables that will achieve the process objectives in an optimal way. In such a scheme the optimizer supervises the setpoints of standard regulatory control loops by providing the optimal path to the controller(s). Because the calculations required for such a control strategy are inherently more complex than those for classical strategies a digital computer is required to implement the model based concept.

The control system structure depicted schematically in Figure 1 allows the controller to adapt to plant disturbances and/or to accommodate changes in management operating policies. Adaptation is achieved using a model and an estimator using feedback from measurements of the process input and output signals. Based on this information the best controller output can be calculated.
MODEL BASED CONTROL OF A SAG MILL

The SAG mill circuit is part of a 19000 tpd copper/gold plant. A schematic diagram of the SAG circuit and instrumentation is shown in Figure 2. Before implementation of the model based control strategies the circuit throughput was verified for the proposed control strategy comparison.

Two strategies were developed for comparison with the manual control used in the plant. The first strategy, SuperSAG, calculated the feedrate from an equation similar to a PI feedback controller involving mill power. The second strategy, model based, uses the mass balance model to calculate the feedrate that will result in a specified mill power. Table 1 shows predicted performance of the SAG circuit from dynamic simulations. Table 2 summarizes actual plant performance.

TABLE 1. Prediction of SAG Mill Control System Performance

<table>
<thead>
<tr>
<th>Feedrate, mtph</th>
<th>Manual</th>
<th>SuperSAG</th>
<th>Model Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mill Power, kw</td>
<td>5004</td>
<td>5540</td>
<td>5725</td>
</tr>
<tr>
<td>Energy, kwh/mt</td>
<td>5.88</td>
<td>5.92</td>
<td>5.98</td>
</tr>
</tbody>
</table>

TABLE 2. Plant Evaluation of SAG Mill Control System Performance

<table>
<thead>
<tr>
<th>Feedrate, mtph</th>
<th>Manual</th>
<th>SuperSAG</th>
<th>Model Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mill Power, kw</td>
<td>4761</td>
<td>5034</td>
<td>5020</td>
</tr>
<tr>
<td>Energy, kwh/mt</td>
<td>5.30</td>
<td>5.30</td>
<td>5.17</td>
</tr>
</tbody>
</table>
The predicted plant capacity under SuperSAG and model based control strategies are remarkably close. The increase in operator performance for the plant evaluation is a result of the operators learning from the expert control strategies. Figure 3 shows a histogram of SAG mill feedrate under manual and model based control. The increase in throughput was 14%. This plant has been using the model based strategy for the last two years with 95% availability.

**OPTIMAL CONTROL OF A ROD/BALL MILL CIRCUIT**

The optimal control of a rod mill/ball mill grinding circuit in a copper ore concentrator is reported by Herbst et al. (1988). That application, discussed below, had the objective of replacing the existing supervisory PI control loops with an optimal control multivariable control law to control slurry volume in the sump and product particle size.

**The Grinding Circuit**

The grinding circuit consists of an open-circuit rod mill followed by two closed-circuit ball mills in parallel (Figure 4). All three mills are overflow discharge types. The two hydrocyclone banks that feed the ball mills each contain four hydrocyclones.

Each of the grinding circuits in the concentrator are under the control of a Fisher Provox™ system, which is based partly on its microprocessor card controllers and on an HP 1000F minicomputer that performs the optimal control. The optimal value of feed is downloaded to a microprocessor card responsible for maintaining the feedrate at setpoint. Since no measurement of sump water addition is available the optimal value of sump water is converted to percent value opening and then downloaded to a positioner loop.

**Optimal Control**

The objective of this study was to maintain the controlled variables at setpoint. This can be accomplished by finding the sequence of optimal inputs that minimize a chosen performance index; for example, maintaining the circuit product size as close to the setpoint as possible at all times.
Plant Testing

The optimal control strategy was programmed in the FORTRAN language on the HP 1000F minicomputer at the plant. A flowsheet of the program is shown in Figure 5. The optimal values of feedrate and sump dilution water were transmitted from the host minicomputer to the distributed controller.

Programming of the computer and calibration of instrumentation required about 3 months. Because of the pending shutdown of the plant, some of the expected instrumentation was not installed. The actual test of the strategy occurred in the two day period prior to shutdown. Unfortunately, the plant performance was rather erratic during this period. As a result there were only a few hours during which the plant and strategy were operating satisfactorily. The data from this period are presented in Figure 6, which shows some of the Kalman filter estimates and in Figure 7 which is a comparison between the optimal control strategy and another grinding circuit under conventional PI control. Here the feedrate, product size and sump are plotted for the grinding line optimal control (dotted line) and another grinding line under conventional PI control (solid lines). A histogram of the data in Figure 7 is shown in Figure 8. The histogram shows the significant reduction in variance and the smaller mean particle size under optimal control.

SUPERVISORY CONTROL OF A BALL MILL GRINDING PLANT

This copper ore grinding plant has a capacity of 72000 tpd and consists of 12 grinding lines in which each 16.5' x 24' ball mill is operated in closed circuit with four 18' hydrocyclones. The objective of the control system was to maximize plant throughput while maintaining an acceptable product size. Whenever the maximum feedrate constraint was encountered, the size setpoint was reduced to minimize product particle size.

Control hardware consisted of an industrial IBM PC with the 80386 microprocessor, 4 MB of RAM, 2 20MB hard disks, EGA graphics monitor, IBM serial/parallel adapter and an Opto 22 serial I/O network.
Control software included ONSPEC control package for dynamic displays, historical data logging and trending and I/O communications. Ball mill model, estimation and control strategies ran concurrently with ONSPEC on a multi-tasking operating system.

Control actions were implemented through an expert system which used information provided by the instrumentation and Kalman filter. Two levels of control were tried. Level I increased the feedrate a specified amount if no emergency conditions existed and either cut the feedrate or took no action depending on the emergency. Level II modified the feedrate increases or decreases depending on the trend of ore hardness as estimated by the Kalman filter.

Plant instrumentation consisted of PSM particle size analyzers, ultrasonic sump level detectors, flowmeter and density gauge and feedrate measurement.

A performance comparison over four months of operation with model-based control resulted in a 10% capacity increase in the plant. Figure 9 shows a histogram of average mill throughput for the standard plant control strategy and model-based expert system control. Power consumption per ton of ore averaged 7% less with model-based control, as shown in Figure 10.

**FEED FORWARD SUPERVISORY CONTROL OF A FLOTATION CIRCUIT**

Flotation circuits are difficult to control because of the large time delays between the manipulated and controlled variables. Disturbances such as flotation changes may not be acted upon until well after the initial onset. The strategy described below used information from the first two cells of the flotation circuit to predict, with a model, the behavior of the rest of the circuit. By getting early information on disturbances it is possible to take corrective action before the rest of the circuit is affected severely. This strategy contrasts sharply with the model based strategies of grinding where the effects of disturbances appear more rapidly.
The Flotation Circuit

A schematic diagram of a flotation circuit at a copper ore concentrator is shown in Figure 11.

Estimation Scheme and Verification

The Kalman filter has been developed for the first two cells (Herbst, Hales, Zaragoza, 1986). The flotation rate parameters were estimated on-line since these varied with the ore's flotability.

Measurements during a 36 hour period from the manually controlled plant were collected and stored for later analysis with the Kalman filter. An example of estimation with the filter is shown in Figure 12 which shows excellent agreement between the prediction and measurement of copper grade in the scavenger tails. The measurement of copper in the scavenger tails dropped out for two periods but the filter was able to provide a stable estimate during this period.

Feed Forward Control Strategy

The estimate of ore flotability obtained on-line for the first two cells can be used in model equations for the rest of the circuit to predict the steady state recovery and grade values as the flotability changes. This capability is exploited in a strategy in which the steady state values of frother addition, collector addition and pulp level that minimize an economic performance index are determined. The performance index involved the recovery of copper, the concentrate grade and the cost of reagents.

A comparison by simulation between PI control and the feedforward strategy is shown in Figure 13 for the case in which the flotability of the feed ore changes periodically. The feedforward strategy does much better at
controlling the recovery since it anticipates the effects of the changes in flotability and acts against them much sooner than the PI strategy.

**SUMMARY AND CONCLUSIONS**

In addition to the examples presented here, the authors and co-workers have applied the Kalman filter to crushing circuits (Herbst and Oblad, 1985) agitation leaching (Asièhene, 1986) and grinding ball wear (Herbst and Wardell, 1986). The wide range of fundamentally different processes to which model based control techniques may be applied demonstrates the power of model based control.

Model based control does require a somewhat substantial investment of time and effort especially in developing the models. The filter and control strategy must also be tuned, which is the process whereby the freely chosen filter parameters are adjusted until the estimation and control performance levels are optimal. The earliest applications required the largest effort since little in the way of software was available. Since that time, software for model estimation and control calculations has become much more available.
REFERENCES

Asihene, S.W. (1986). Ph.D. work in progress, Department of Metallurgy, University of Utah, Salt Lake City, Utah.


Figure 1: Schematic representation of model-based control strategy

Table of Symbols:

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP</td>
<td>Bearing Pressure</td>
</tr>
<tr>
<td>D</td>
<td>Density</td>
</tr>
<tr>
<td>F</td>
<td>Flow</td>
</tr>
<tr>
<td>FC</td>
<td>Flow Controller</td>
</tr>
<tr>
<td>L</td>
<td>Level</td>
</tr>
<tr>
<td>P</td>
<td>Power</td>
</tr>
<tr>
<td>VS</td>
<td>Variable Speed Drive</td>
</tr>
<tr>
<td>W</td>
<td>Weightometer</td>
</tr>
</tbody>
</table>

Figure 2: Configuration of SAG Circuit

Figure 3: A Histogram of SAG Mill Feedrate Under Manual and Model-Based Control.
Figure 4: Rod/ball mill circuit and instrumentation

Figure 5: Flowchart of on-line optimal control program
Figure 11: Flotation circuit and instrumentation

Figure 12: Kalman filter estimation using flotation plant data.
Figure 8: Kalman filter estimated during optimal control test

Figure 9: Comparison of optimal and conventional PI control
Figure 8: Histogram of data from optimal and PI control.

Figure 9: Histogram of Ball Mill Feedrate for Manual and Expert Control.

Figure 10: Histogram of Ball Mill Power for Manual and Expert Control.
Figure 15: Comparison by simulation of optimal and PI control