Remote and Distributed Expert Control in Grinding Plants

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Abstract:

Since the first experiments with computerized expert control of grinding plants in the early 1970's expert control has steadily progressed in the minerals industry to be very advanced, including not only many artificial intelligence methodologies but advanced computing and measurement systems. A 1970's expert system will be compared with the latest systems used in the industry along with performance comparisons. The most advanced systems today use real time image systems as well as acoustic systems that listen to the grinding process within the mill to further understand the process of grinding in large mills.

Expert Computer Control In The 1970's

Computer based control in the 70's was an experiment. Debate centered on whether or not direct computer control (DCC) was advisable or foolish. Distributed Control Systems (DCS) were new on the scene and most grinding plants were still controlled through relay panels and single analog loop controllers. Computers were expensive with operating systems that were complex and not necessarily designed for real-time applications. Databases were monolithic and only existed on "main-frame" computers. Artificial intelligence was still buried deeply in the research areas of a few Universities and was still a fanciful dream of fiction writers. Grinding plants were still small by today's standards and included two and three stages of crushing, primary ball milling and secondary rod milling. Semi-autogenous grinding mills were in development and debate raged over all aspects of their utilization.

These facts were only technical details, however, to those studying grinding, its costs and the benefits of improving its efficiency and the capacity of existing grinding lines. At the time it was believed that the energy efficiency of ball mill grinding was as low as 3 to 5 percent which provided plenty of impetus for experimentation with installing computers in mineral processing plants and then writing supervisory control programs that would monitor the performance of the grinding plant then calculate new process set points and sent them out to the underlying control system for implementation.

Ray Mines Example

In the 1970's Kennecott owned multiple mineral processing plants in the United States and maintained a world-class process technology center. One of the chartered responsibilities at the Process Technology Center was to understand, develop and implement world class process control systems and strategies at each of its operations. The groups cutting edge skills with computers made it very natural to install a computer with a real-time operating system at Ray and begin the process of interfacing it to the underlying control system. Grinding line 5 was selected because it had one of the very first particle size analyzers manufactured by Autometrics installed.

The original program written to monitor the state, or performance of the grinding line was written in the Basic programming language and data collected by the system was actually stored in digital format on a regular portable cassette tape recorder. This was pretty rudimentary but innovative and effective. The computer was housed in a wooden cabinet and connected to a custom interface set of electronics to ultimately interact with Foxboro single loop analog controllers as is shown in Figures 1 and 2.

Figure 1. Supervisory Control Computer in a Wooden Box, Circa 1978

Figure 2. Rudimentary Single Loop Analog Controllers Installed on Milling Floor Right Next To Grinding Mills

Operator Mimic

The phrase "Operator Mimic" was selected as the title of the computer control program written to monitor the grinding line and then calculate new process set points to be automatically implemented by the single loop controllers. The control objective was to maximize the throughput rate and minimize the final particle size. Experiments were run to determine the best underlying control loops to supervise, e.g. control size with water addition to the cyclone feed sump or by adjusting the new feed rate or by the feed density to the cyclones. The cyclone feed pumps were variable speed which was also somewhat unique for the time period.   Once the basic stabilizing control loops were selected the operator mimic expert strategy was implemented and performance was documented with on-off testing and statistical analysis of the results.

Table 1. shows the terse output of the system that keep the operators informed about the decisions being made and the new set points being sent to the controllers. In this example we see that the condition of the circuit was deemed to be "Low Ore" suggesting that feedrate could not be maximized but that the grind size could be minimized. Ball Mill circulating load was being monitored and particle size set point was being changed when mill conditions permitted.

STRATEGY I TELEPRINTER OUTPUT

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TAPE DUMP 257  6  32  15
LOW ORE <PS> CONTROL  PSSP= 23.5939 PS= 24.1492 CL=58.377 @ 6  36  23  257
OFFSET= .137956 SLOPE=-.447284 B4= .309328
NO ACTION

LOW ORE <PS> CONTROL PSSP= 23.5939 PS= 23.7331 CL= 62.8788 @ 6  44  30  257
OFFSET= .244697 SLOPE= 1.40856 B4= 1.65326
INCREASE PSSP 257  6  44 30
 22.3633  25.3863  28

LOW ORE <PS> CONTROL  PSSP= 25.3863 PS=25.6098 CL= 63.9066 @ 6  52  39  257
OFFSET= .332064 SLOPE= 1.17905 B4= 1.51111
INCREASE PSSP 257  6  52  39
 22.3633  27.121  28
```

Table 1. Minimal System Output via a Thermal Printer for the Operator Mimic Strategy

In spite of the difficult computing environment and rudimentary sensors the strategy was very successful. The on-off testing showed and proved what was believed to be possible before the experiment began. That is, the average throughput rate could be increased while decreasing the average grind size. One interesting finding was that the actual specific energy of the mill decreased which suggest that the actual grinding efficiency increased as a result of the control strategy.

Figure 3 shows the throughput histograms for the grinding line under the pre-existing operator controlled approach versus the operator mimic expert control strategy. The improvement was at the high end of the types of improvements that have been achieved over the years. The plots also clearly show a bimodal dataset suggesting that there were probably two different ore types routinely being processed.

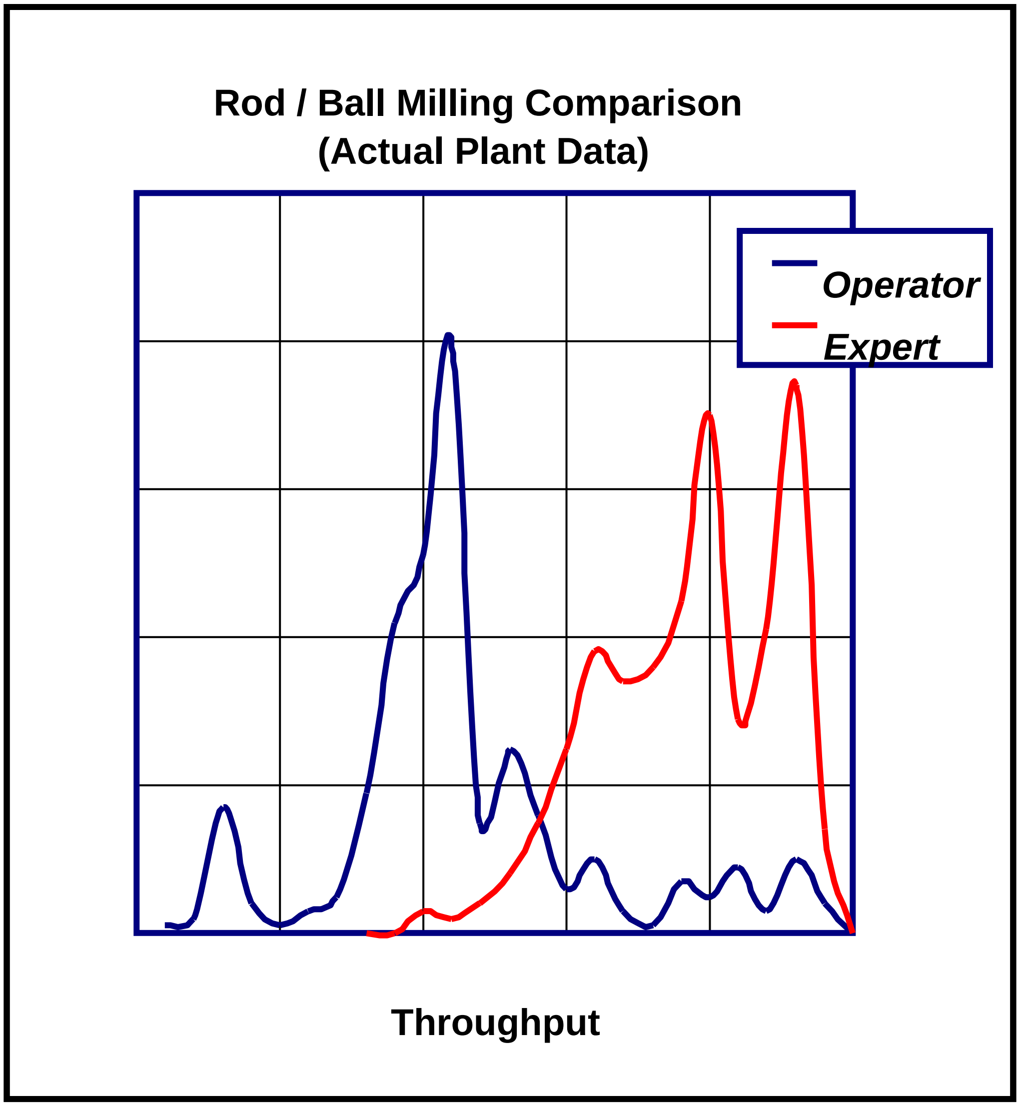

Figure 3. On-off Testing Results of the 1978 Operator Mimic Expert Strategy

Phenomenological Modeling – population balance models

In parallel to the emerging efforts to program computers to monitor and calculate process set points was the academic development of first principle models of the grinding process. At the forefront of this work was Professor John Herbst, then at the University of Utah. Professor Herbst's graduate studies at University of California at Berkley under Professor Douglas Fuerstenau centered on what became known as the "Population Balance Grinding Model."(4) The basis of the modeling methodology was the concept that rocks or particles in a grinding mill had a certain probability of being selected for a breakage phenomenon either with other rocks or the grinding media. Once selected for breakage their resulted a distribution of daughter fragments or particles produced by the event.

Mathematically this concept of the grinding process was represented in a mass balance construct that only needed to have model parameters determined to represent the grinding process. Estimation of these model parameters were made by applying Kalman filtering to the process in real-time (5).

The value, of course, of real-time process modeling lies within the ability to look ahead, or predict the future state of the grinding circuit thereby allowing possible future states of the mill to be taken into account along with the past and current state to determine, based upon expert knowledge, what changes to the process set points will push the mill to more closely achieving the optimization objectives of the circuit. Accurate real-time predictive models expand the possibilities of control to include "asking the model, given where we are (current set points), and our operational objectives what are the best new set points that could be implemented to improve our state in the near future?"

Now, instead of circuit optimization via heuristic expert rules, we have the opportunity for optimization based on model predictions. Incidentally, if the models, either their structure, or their parameters are adjusted dynamically then instead of a static expert control system we now have an adaptive one, that changes over time, or adjusts over time reflecting ore changes or equipment changes.

These population balance models were implemented in the 1980's in a number of plants around the world with fair success . The Kalman filter mathematics are not trivial and required substantial skill and experience to implement which certainly was a barrier to wide-spread use as was the fact that these models were all programmed in traditional computer programming languages in custom programs that suffered from the maintenance problems already identified.

Artificial Intelligence meets Minerals Processing - Expert System Shells

Expert system shells, that began to appear at Universities of the world in the early 1980's, are computer programs that have two specific and unique features: 1) the ability to write rules about a specific domain of knowledge in linguistic terms, and 2) the ability to infer, or draw conclusions about new information given the domain rules of the system.

The ability to record domain knowledge in linguistic terms was a great advancement for the industry because historically there had been many supervisory computer programs written in a variety of programming languages that were successfully implemented in mineral processing plants that fell into disuse after the original creators moved on to new positions or plants. It is difficult for one person to understand the big picture and subtle nuances of a sophisticated computer program that has been written by another. Program documentation is an art that is not practiced by many.

With the formalization of expert system shells several possibilities for overcoming the shortcomings of hard coded operator mimic type supervisory control programs loomed on the horizon. The most immediate problem to be overcome was the fact that the expert system shells that were appearing were not designed to be connected to real-time processes where they would continually cycle through rule-sets to calculate new set points on a second-by-second basis. Two of the company's that immerged first to address this had their roots in metallurgical engineering and minerals processing, Pyramid Resources, now known as KnowledgeScape and Comdale which ultimately failed as a business and was subsequently purchased by ABB. Another entrepreneurial start-up company, Gensym, recognized the opportunity for a real-time expert system and ultimately created a system known as G2. There were others along the way but these were first in the minerals industry.

As an interesting note, the first real-time expert system created by Pyramid Resources was known as RTX. RTX had connections to NASA and a program there called Cerberus which had been created to analyze land-sat photographs. Cerberus was not designed for real-time analysis or control purposes so Pyramid's work to create RTX from some of the underlying technologies in Cerberus was unique. Three minerals plants are still running RTX systems that were installed in the early 1990's.

Examples of mineral processing domain knowledge written in linguistic terms are shown below. Careful examination of the rules suggests that they are associated with ascertaining whether or not a mill is in a classic overload condition or not, where overload is generally defined as a rising bearing pressure or load in the mill at the same time the power to turn the mill is decreasing.

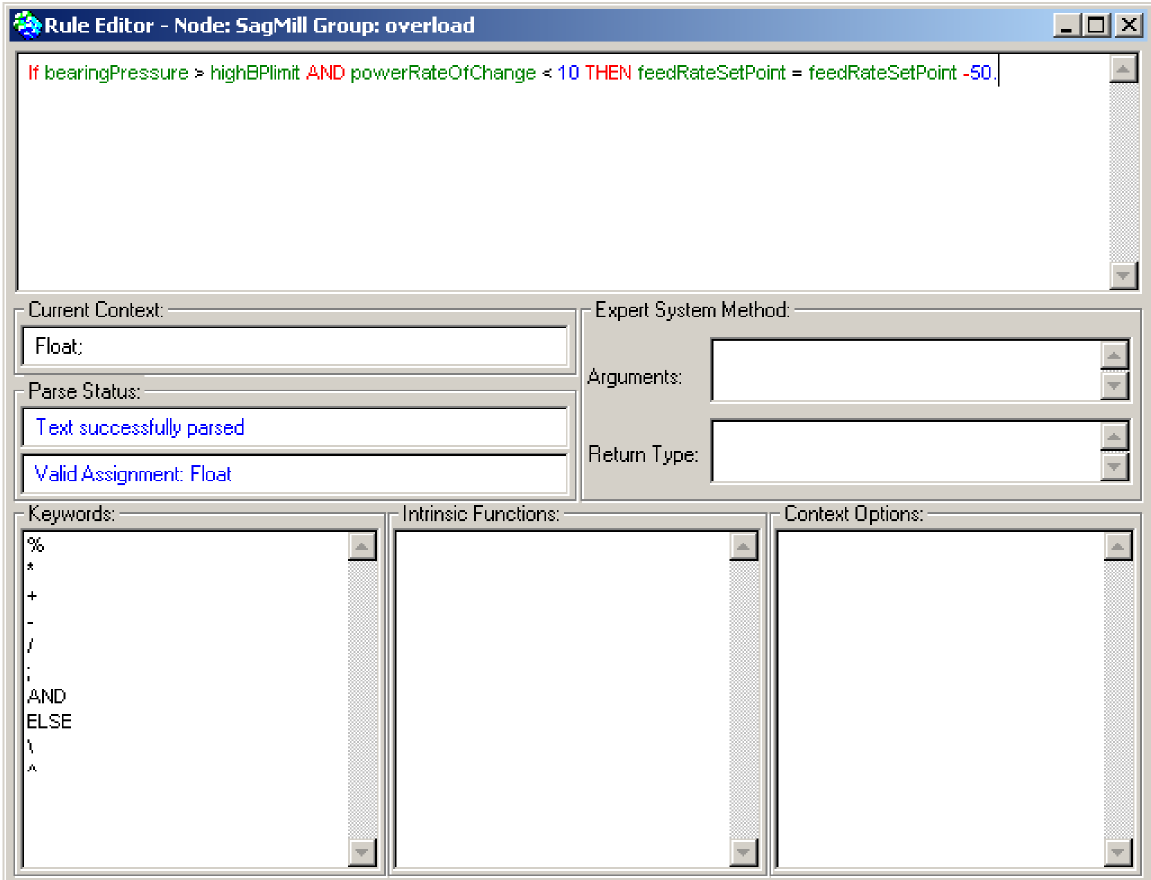

Figure 4. Crisp Rules to Infer a Classic Mill Overload

These types of rules are designed to draw conclusions about the state of a system. Obviously, the person writing such rules needs to know a lot about grinding mills to be able to formulate this type of rule. Another set of rules that also require "expert" knowledge are those that assess the state of a grinding system, and then given a set of control objectives determine a new set of set points that are deemed by the expert to operate the grinding mill in a better way. For example, it is quite common for mill operators to want to maximize throughput rate given physical, metallurgical and economic constraints. Rules that reflect this objective and expert knowledge about grinding are shown below.

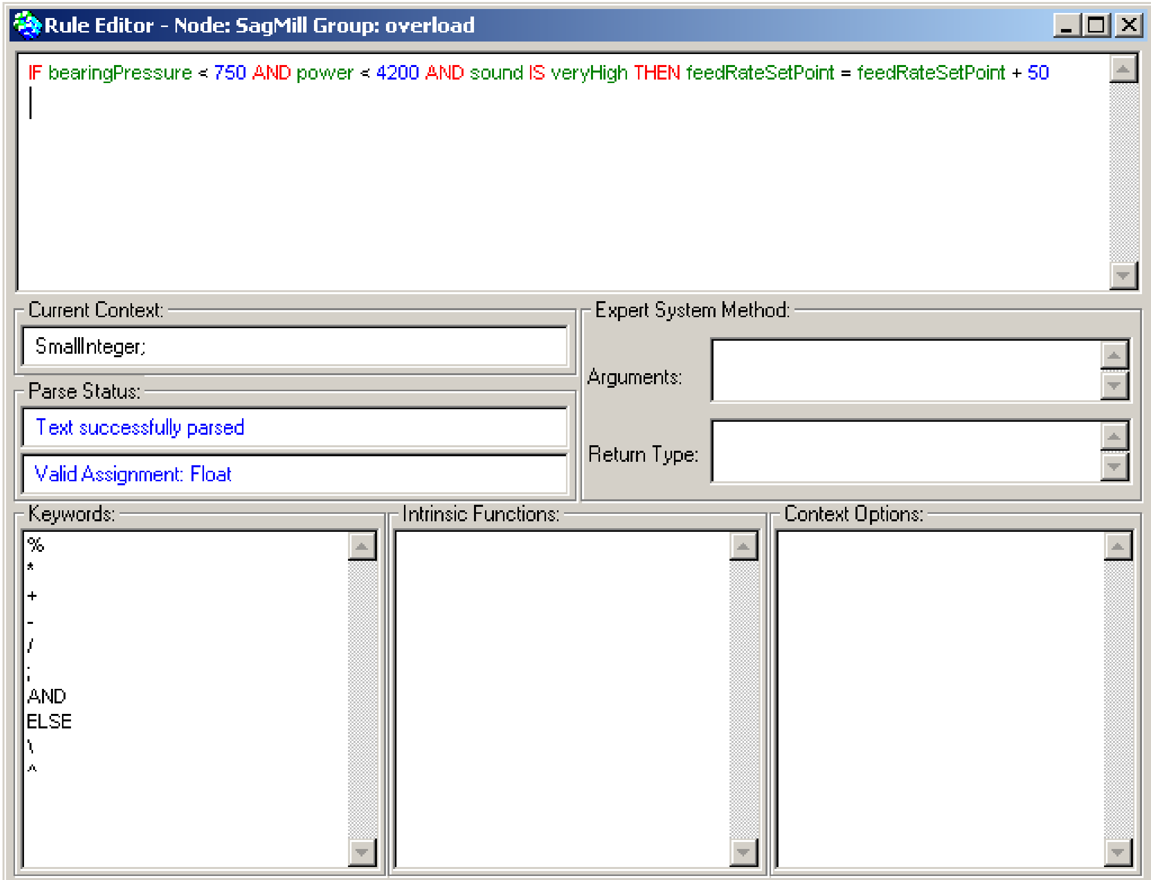

Figure 5. Optimization of Feedrate Rule

Crisp Rules

The rules above are examples of what is termed “crisp rules.” What makes them crisp is the unequivocal nature of the operators, less than, equal to, greater than and the singular numeric constants in the rule. The rule is either entirely true or it is false. The expert systems of the 80’s only utilized crisp rules.

Fuzzy Logic

“Fuzzy logic is an approach to computing based on “degrees of truth” rather than the usual “true or false” (1 or 0) **Boolean** logic on which the modern computer is based. The idea of fuzzy logic was first advanced by Dr. Lotfi Zadeh of the University of California at Berkeley in the 1960s. Dr. Zadeh (2,3) was working on the problem of computer understanding of natural language. Natural language (like most other activities in life and indeed the universe) is not easily translated into the absolute terms of 0 and 1.
Fuzzy logic includes 0 and 1 as extreme cases of truth, or "the state of matters" or "fact", but also includes the various states of truth in between so that, for example, the result of a comparison between two things could be not "tall" or "short" but ".38 of tallness."

Fuzzy logic seems closer to the way our brains work. We aggregate data and form a number of partial truths which we aggregate further into higher truths which in turn, when certain thresholds are exceeded, cause certain further results such as motor reaction. It may help to see fuzzy logic as the way reasoning really works and binary or Boolean logic is simply a special case of it.” (1)

An mill power example is shown in Figures 6 and 7. Here mill power is defined in the fuzzy terms “very low”, “low”, “average”, “high”, and “very high.” An example rule that uses these fuzzy values is in the following figure.

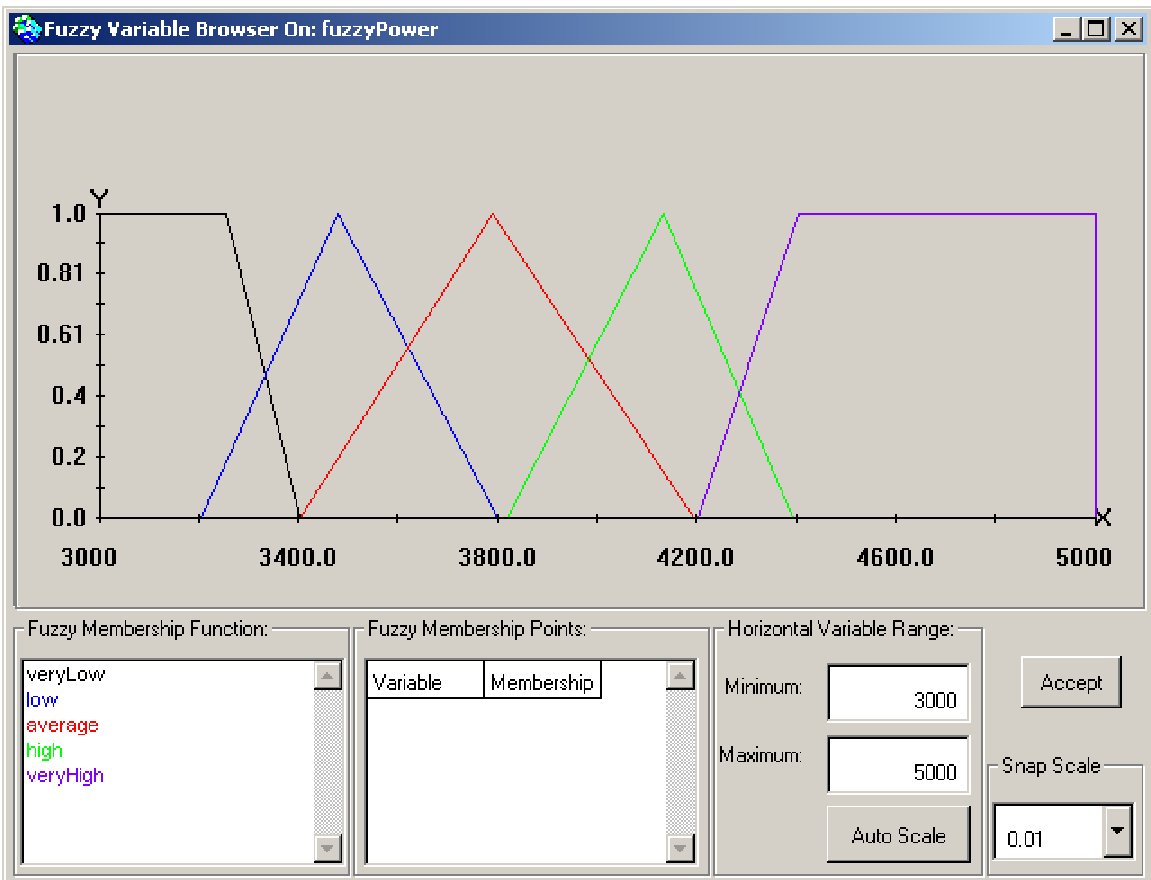

Figure 6. A Fuzzy Set for Sag Mill Power

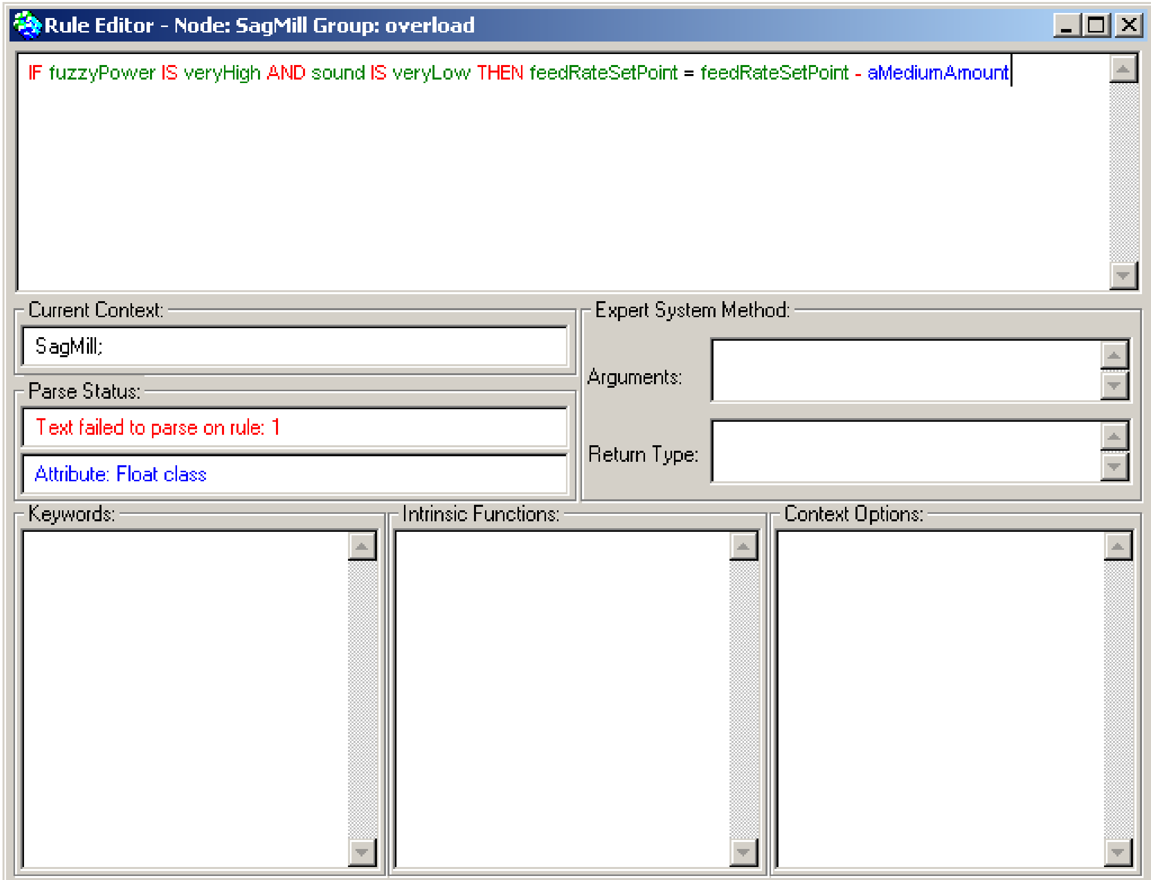

Figure 7. Fuzzy Rules Utilizing the Fuzzy Representation of Power

Neural Network Models

The advent of the population balance grinding model created a lot of hope and expectation regarding on-line adaptive modeling of grinding mills. Its complexity and the nature or lumping unknown phenomenon into the error function and the complexity of the model parameter adaptation proved to be quite challenging in a practical sense. After the advent of this modeling approach several first principle modeling approaches were made for the flotation process (7). Again, some success was achieved in actual plant trials but widespread industrial utilization was not achieved.

The difficulties discussed above left a void for a generalized non-linear modeling technique suitable for minerals processing unit operations that was flexible and understandable by a wider audience. Artificial Neural Networks (ANN) or just neural network (NN) has proven to be one such modeling process. The origin of the science of neural networks can be traced back to ancient times, but the real investigations started with the work of McCulloch and Pitts in 1943 (9).

From Wikipedia (8), an artificial neural network, is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. There is no precise agreed definition amongst researchers as to what a neural network is, but most would agree that it involves a network of relatively simple processing elements, where the global behaviour is determined by the connections between the processing elements and element parameters. The original inspiration for the technique was from examination of bioelectrical networks in the brain formed by neurons and their synapses . In a neural network model, simple nodes (called variously "neurons", "neurodes", "PEs" ("processing elements") or "units") are connected together to form a network of nodes — hence the term "neural network".

Like the brain, an artificial neural net is a massively parallel collection of small and simple processing units where the interconnections form a large part of the network's intelligence. Artificial neural networks, however, are quite different from the brain in terms of structure. For example, a neural network is much smaller than the brain. Also, the units used in a neural network are typically far simpler than neurons. Nevertheless, certain functions that seem exclusive to the brain, such as learning, have been replicated on a simpler scale with neural networks.

These concepts are shown in Figure 8 below where the concept of modeling the future state from the recent past is show. This is exactly how neural networks are commonly used in grinding applications.

Figure 8. Neural Network Conceps

Modern Expert Control of a Large Grinding Circuit

Expert control systems in a modern Sag Mill Plants have evolved into robust, stable and highly available systems. They tightly integrate all of the unit operations into a plant wide control strategy that continuously stabilizes the process, and then searches for optimum set points based on metallurgical principles and best practices. Most modern expert system shells employ an object oriented approach. Object oriented programming is a software development paradigm that has become popular in recent years, and allows you to represent in software a better model of the domain, and the problem that you are trying to solve. Rather than create a program that is a monolithic set of instructions for the computer, the developer can create a system of objects, which can contain both state and behavior. These objects represent real world entities and interact with one another. This allows the expert strategy developer to program intelligence into the software representation of each piece of equipment. The equipment can then look after itself, searching for the best operating conditions. When a certain piece of equipment or circuit becomes a bottleneck for the process, it can signal upstream equipment or circuits which react accordingly to remedy the situation.

The modern expert system in a mineral processing plant will integrate all of the unit operations in a manner that achieves the financial objectives of the plant. This profit optimization provides tremendous value to the plant with little associated cost. An example copper sulfides plant will be analyzed. A modern copper plant would include one or more lines of Sag mills, each feeding two ball mills. The ball mills operate in closed circuit, with cyclone overflow feeding a flotation plant. The diagram below illustrates the plant layout.

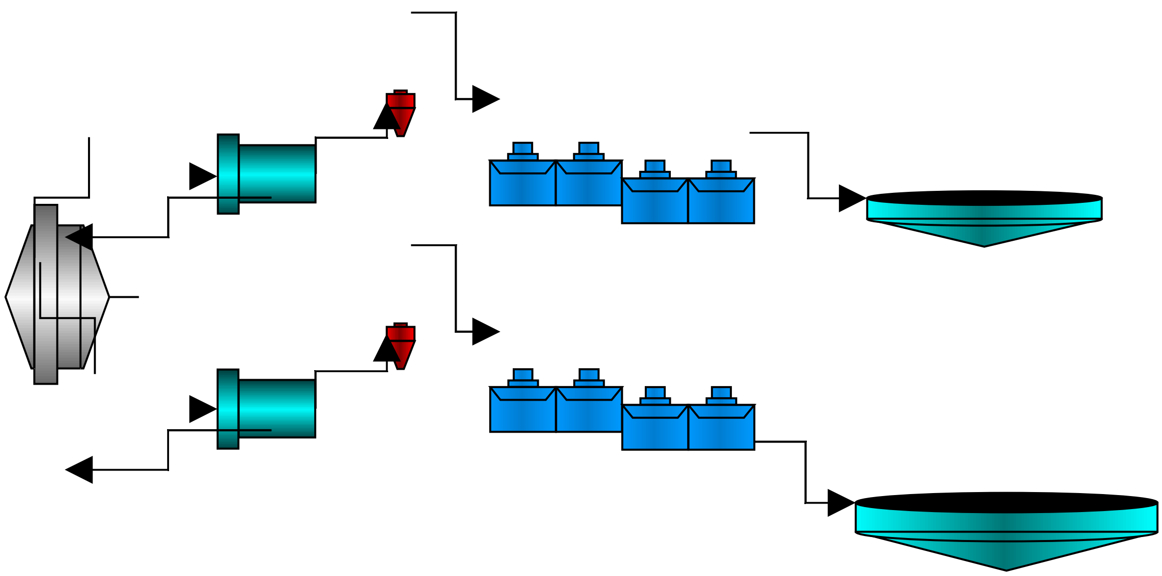

Figure 9. Pictorial Representation of Modern Grinding and Flotation Plant

The overall goal of the plant is maximum copper production at acceptable concentrate grades. The result is a combination of feed rate and the recovery and cleaning ability of the flotation circuit. Experience has shown us that the best way to achieve the plant wide goal is to allow the unit operations to work independently towards their specific goal and interact when necessary. When those unit operations cannot maintain a certain level of production they may communicate with upstream processes to find a joint solution.

In this example plant, the unit goals can be broken down like this:

- Sag Mill – maximum throughput
- Ball Mill – target grind size
- Rougher – maximum recovery
- Cleaner – target concentrate grade
- Scavenger – maximum recovery

When allowed to work towards these individual goals, the plant-wide goals may be achieved. If one of the units cannot achieve a minimum requirement, it may then signal upstream processes to help.

For example, a Ball Mill circuit strategy will try to maintain a target grind size. The strategy will adjust sump water, underflow water, cyclone pressure and pump speed to maintain the grind size. When all of the control actions are exhausted, the ball mill circuit will signal the sag mill circuit that it is overloaded, and the sag mill strategy will react properly. It will change its operating parameters to provide more attrition grinding, and alleviate the overload of the ball mill circuit. If the overload is not reduced then the total feed rate will be reduced.

Another example would be in the flotation circuit. A set of columns would adjust their air, pulp level and wash water settings to obtain the target concentrate grade. If after making all possible changes, the minimum grade is not achieved, the cleaner circuit can then communicate with the rougher circuit to negotiate a solution. The response of the rougher may be to make changes in its settings to increase its own concentrate grade, facilitating the cleaner circuit to achieve its minimum requirements.

This system of interaction between units allows for the highest level of plant optimization. In the unit operations' individual strategies, all of the previously described technology is implemented as necessary. This may include rules, fuzzy logic, neural network models and optimizers. The implementer will use all of the technology available to achieve the goals of the plant.

An example of this would be the integration of technologies in the Sag mill strategy. The sag may have a set of rules designed to react to emergency situations like mill overloads, high mill power or excessive recycle rates. These may be implemented using crisp logic. If no emergency conditions exist, the strategy may try to maintain stable operating conditions while trying to gradually move the mill to its most efficient operating conditions. This is done by changing the mill feed water and the mill speed. This could be done using fuzzy logic, to provide a smooth control response while taking into account multiple variables. At the same time neural network models may be running to help select the best possible set points and limits using modern sensors like microphones and image analysis that provide valuable information but are hard to write direct rules for.

In the modern expert system, we use many forms of artificial intelligence tools to build individual unit strategies, and the object oriented interaction of those strategies provides a robust global optimization strategy for the plant. This provides significant benefits to the plants using them, and gives a framework for control that will endure for many years to come. When running correctly the control system will assure that the plant is running at its full potential and is only constrained by real physical bottlenecks. Over time these bottlenecks can be identified and addressed, and a continuous cycle of plant improvement can be achieved.

Industry Challenges – Three Problems

Three problems have plagued our industry since the inception of using computers to monitor and calculate process set points. The first, process understanding seems, counter intuitive since we are all process professionals, that is, metallurgical engineers, mineral processors and experienced mill operators. The problem is that our education isolates mineral processing into individual pieces where cause and effect can be neatly delineated, whereas the reality of plant production is a complex multivariable, ever changing environment where nothing exists in isolation from all other elements of the process, ore conditions and equipment conditions. Mineral processors are not conversant with modern artificial intelligence theory and practice. Neural networks, genetic algorithms, swarm optimization, induction rule tree discovery, fuzzy logic for example are not even partially understood by the common mineral processing engineer. Finally, our personnel problem is complicated by the relatively remote locations of minerals processing plants throughout the world and the fact that drawing qualified people to these remote locations for extended periods of time has been and will always be a challenge.

The second, is that minerals processing professionals are mobile, moving somewhat frequently from one employer or position within the organization which is compounded by the constantly expressed opinion that most processing facilities are understaffed. It is not uncommon for one or more plant team members, from management to implementer, to leave or join during the design and implementation of an advanced expert control project, not to mention the maintenance and use of the technology over the long term life of the project.

The third, problem is that computer control, programming, computer operating systems, networking etc. are complex and traditional educational training barely touches on these essential areas. This problem is also compounded by the fact that whereas there are too few professionals in our plants, there are even fewer who are proficient in both the complex reality of mineral processing and the complex reality of modern computing hardware and software.

Because these problems have been present ever since the inception of expert control and the inherent need for improved processing efficiencies, as well as improved coordination between all the plant parts new technology is slowly being introduced to further transform the monitoring and control of mineral processing plants.

Distributed and Remote Control

Long range connection to expert control systems has been routinely done since the earliest days of experimentation and installation. Regular telephone modems were used for many years. Of course, communication speeds and greatly varying telephone line quality throughout the world greatly hampered the functionality and success of this methodology. With the advent of the internet and the emerging wide-spread speed increases of this technology it is now possible to connect to plant expert systems via the internet and greater and greater speeds. This has opened up a whole new possibility to further improve the performance of expert control systems as well as minimize the impact of the three problems just discussed.

The Near Term Future – Long Range Distributed Control

In their advertising, Sun Microsystems coined the phrase "The Network Is The Computer." This embodies the concept that we believe will become prevalent in the near future, that is, long distance extensions to the plant expert control system to a "virtual control room" located in remotely in a convenient city with ample personnel resources. In this remote location a subtle shortcoming of many minerals plant expert systems will also be improved. That is, many expert systems are somewhat static in nature. Once they are designed, installed, tested, and adjusted, they are left "as is" for long periods of time. The problem here is that additional improvements are always possible if there is a process in place to measure performance, analyze data and further design improvements. If you visualize a shape of a normal distribution or the "bell curve" the bulk of most grinding expert systems naturally and appropriately centers literally around the mean ore and equipment conditions. In total there are still substantial gains to be found and mined on both sides of the distribution of conditions.

With newer, affordable, higher speed internet connection technology remote expansion of the plant expert control system will facilitate the next generation of plant performance improvements. This next wave of development and improvement will require a different type of trust to be developed between plant operations and the remote locations. This will be accomplished because of the sound business issues driving continued improvement and a recognition of the barriers that prevent continued improvement limited to plant site only.

Lastly, the establishment of remote virtual control rooms will allow a newer technology, "Data Mining" to enter into use and be applied to further improve mineral plant performance. Vast quantities of process data accumulated via the real-time expert control systems are, by in large, not used with defined processes to further improve expert systems once they are up and running.

Simply put, data mining is the "mechanized process of identifying or discovering useful structure in data (7)." The objective being the knowledge discovery associated with the process of analyzing large collections of process data, cleaning and filtering the data, organizing the data and then statistically analyzing it to reveal and explore any deep and potentially profitable relationships that were not previously identified or understood.

Conclusions

There has been a steady march to improve control of the complex grinding processes used in minerals processing. Each new sensor, computing, analysis and visualization methodology has found its way into he mix of tools to better understand and control grinding. The result of this is the tightly integrated control of grinding using many of the artificial intelligence tools available today. There remains however, much more to do. With each new implementation we learn that we can do better and that there are still many shortcomings. As technology continues to progress at astounding rates, the “human factor” becomes the rate limiting factor for continuous improvement of control in the plant. Continuous remote monitoring, and assessment of performance by a cadre of qualified engineers utilizing high speed data mining methodologies will surely be one of the next steps used to identify additional improvements that can be achieved in the grinding process.

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