Using Fuzzy Control to Optimize SAG Mill Production

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INTRODUCTION

While used very successfully in process control for some time in Japan [Fur94] fuzzy logic is still relatively new in other parts of the world. This paper describes some of the workings of fuzzy logic and demonstrates the basics of a fuzzy SAG mill control system.

Although, while relatively unknown, fuzzy control systems have already proven their value in a number of grinding control systems as compared to more traditional crisp expert control systems. This partially due to the fact that fuzzy logic is naturally easy to understand and maintaining a control strategy specified in fuzzy logic is quite straight forward.

Another advantage of fuzzy logic is the ease in which it can be integrated with other artificial intelligence methodologies such as, neural networks and genetic algorithms. Used in conjunction with these technologies fuzzy logic can be thought of as the glue that binds all of the technologies together and controls how they work interact with each other to optimize mineral processing applications.

HOW FUZZY LOGIC WORKS

Fuzzy logic shifts traditional numeric analysis towards a systems approach based on linguistics. This brings about a shift from a focus on representing dependencies from difference and differential equations to fuzzy if-then rules in the basic form of *if* X *is* A *then* Y *is* B where X and Y are linguistic variables and A and B are their linguistic values. For example, *if* bearing pressure *is* high *then* mill sound *is* low. It can be see that this type of descriptive mathematics can be used to characterize imprecise dependencies, or non-linear and complex [Zadeh] systems such are commonly found in mineral processing unit operations.

This so called calculus of fuzzy rules was originally invented by Lotfi Zadeh [Cox] to aid us in both reducing as well as explaining system complexity. Zadeh stated that “as the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance, or relevance, become almost mutually exclusive characteristics.”

Cox further states that in Zadeh’s “view of modeling complex systems, the underlying mechanics are represented linguistically rather than mathematically. Zadeh makes a case that humans reason not in terms of discrete symbols and numbers but in terms of fuzzy sets. These fuzzy terms define general categories, but not rigid, fixed collections. The transition from one category-concept, idea, or problem state-to the next is gradual with some states having greater or less membership in the one set and then another.

Specifically, the concept of fuzzy sets is quite simple. Fuzzy sets are functions that map a value that might be a member of the set to a number between zero and one which indicates its actual degree of membership. A degree on zero means that the value is not in the set and a degree of one means that the value is completely represented by or in the set.

To illustrate consider the concept of a *full* sump. The membership function for the fuzzy set *full* is shown in Figure 1. The fuzzy set indicates to what degree the sump is full based on its level measurement. As the level increases our belief that the sump is full also increases. This is shown in Figure 1 below.

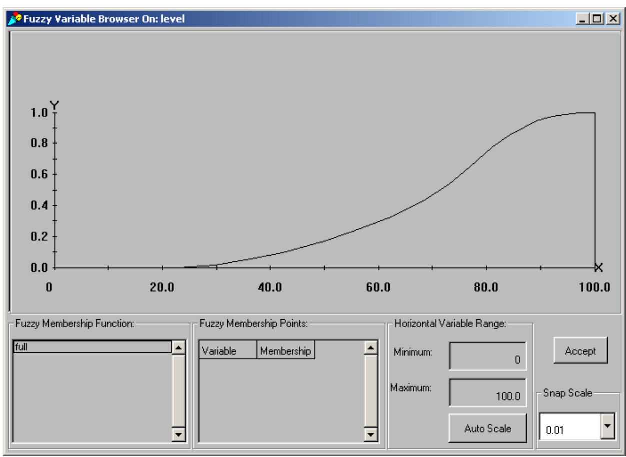


Figure 1. Fuzzy Membership Function For the Fuzzy Concept of Full

The concept of fuzzy sets allow the control engineer to write expressive statements about processes and their state variables that directly express the shades of semantic meanings used by experts. For example, one operator may describe a sump that is seventy-five percent full as medium full whereas another operator may describe it as completely full. *Medium* and *completely* are both fuzzy phrases that are used to describe the exact same level in the sump.

Sag Mill Example

To illustrate the power of fuzzy logic we will next look at its application in controlling a typical sag mill circuit as is shown in Figure 2.

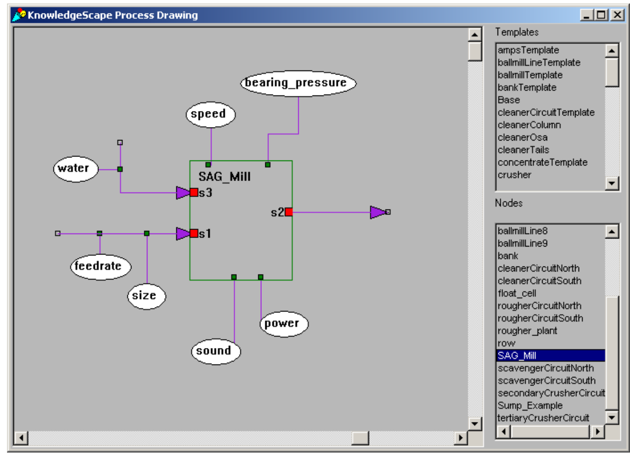


Figure 2. Typical Sag Mill Configuration as Defined in KnowledgeScape.

An example of controlling SAG mill speed will be used to further illustrate how fuzzy logic works. Two simple fuzzy rules are:

> **Rule 1: If sound is low, then speed is increased.**
> **Rule 2: If sound is high, then speed is decreased.**

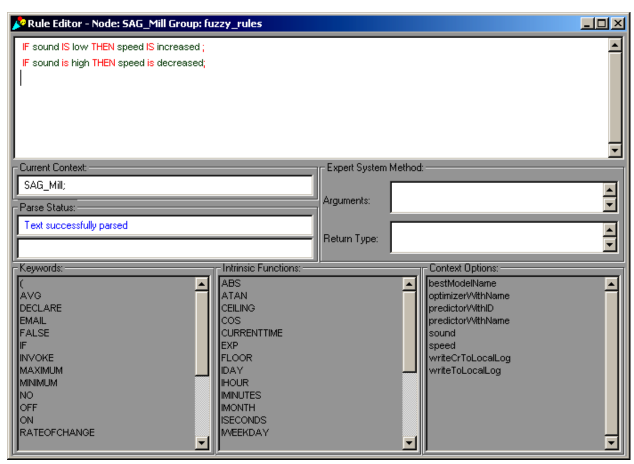


Figure 3. Fuzzy Rule Definitions

In this case, the rules are built upon the semantics of sound being either *high* or *low*. This is shown in Figure 4 below.

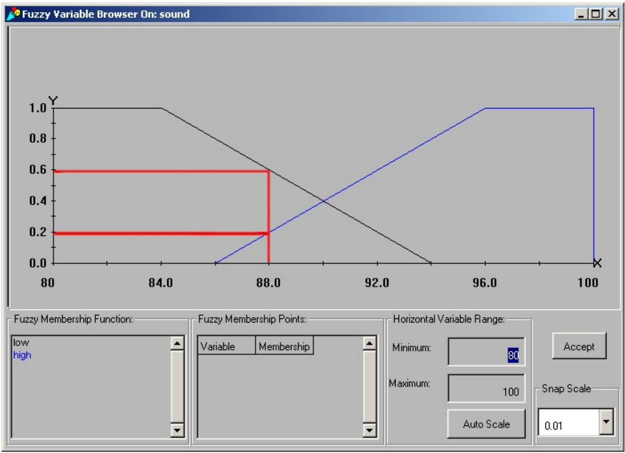


Figure 4. Fuzzy Set Definitions for Sound

Interpreting fuzzy sets is simple. Figure 4 shows the fuzzy sets definitions for both *low* and *high* sound. When the sound is at or below 84 decibels the sound is deemed to be 100 percent low. Conversely when sound is at 96 decibels or above it is deemed to be 100 percent high.

Things get interesting when sound is between 84 and 96 decibels. When sound is at 88 decibels the fuzzy definitions for *low* and *high* indicate that the sound can be thought of as both *low* and *high*. Or, specifically at 88 decibels the sound is ~59 percent low and ~19 percent high as is shown by the red intercept lines on Figure 4.

The fuzzy definitions of speed is *increased* and speed is *decreased* are shown in Figure 5.

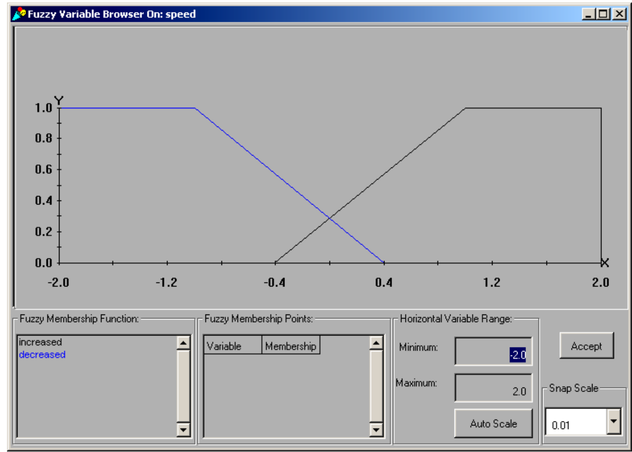


Figure 5. Fuzzy Set Definitions for Speed Increased and Speed Decreased

By evaluating each sound and speed rule individually to determine the degree of truthfulness of the rule and then combining the results, using fuzzy mathematics, ultimately allows us to determine the actual change in mill speed. This means that all changes in mill speed are based on some combination of the conclusions 'speed is decreased' and 'speed is increased.'

Fuzzy Mathematics

In the simplest form there are two ways that fuzzy variables are interpreted, depending upon whether the fuzzy variable is used as part of a condition, or part of a conclusion of an if-then rule statement.

IF <condition> THEN <conclusion>

Fuzzy conditions determine which truth value corresponds to a particular real number whereas fuzzy conclusions determine which real number corresponds with a particular truth-value.

FUZZY CONDITIONS

The purpose of using the fuzzy condition is to evaluate the degree of truth of a given statement. Fuzzy variables are described geometrically and each shape is called a fuzzy set. The shape of the fuzzy set shows the relationship between the hard (real-world) number and its corresponding truth-value.

These fuzzy sets convert numbers into a linguistic semantic. The horizontal axis is the engineering number, and the vertical axis indicates the degree of the truth of a condition for a fuzzy set.

The condition of Rule 1 ('If sound is high') is ~19% true, so the truth-value associated with the conclusion ('then speed is decreased') is also 19%. Rule 2 is ~59% true. These percentages will be used in the next step where they are defuzzified into engineering numbers (e.g., speed changes).

FUZZY CONCLUSIONS

After evaluating each fuzzy rule condition to determined it's degree of truthfulness we evaluate the conclusion to determine the actual output of the rule. As before, the fuzzy variables are represented geometrically with the engineering number on the horizontal axis, and the truth value on the vertical axis is shown in Figure 5.

Whereas fuzzy conditions use the edges of the shapes to determine the relationship between engineering numbers and truth values, fuzzy conclusions use the whole area of the fuzzy set.

The truth value determines the height at which the fuzzy set is truncated. The center-of-mass of each fuzzy set is combined using a weighted-average lever rule to determine an over-all response.

Figure 6 illustrates this. The 'sound is high' condition is ~19% true, while the 'sound is low' condition is ~59% true.

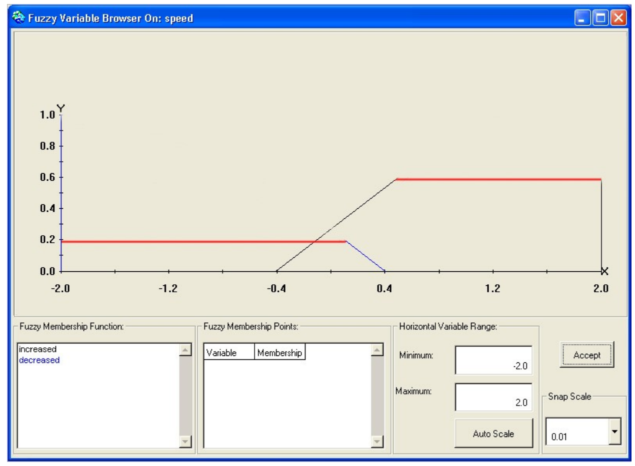


Figure 6. Truncated fuzzy sets used to determine the output of the two fuzzy rules

To determine the actual change in mill speed the following formula is used. The areas and centers-of-mass are calculated and a weighted average is calculated.

$$\frac{(Area\,1)\,(Centroid\,1) + (Area\,2)\,(Centroid\,2)}{Total\ Area}$$

The net result of the weighted response is to increase the speed of the mill by 0.61 RPM.

$$\frac{(1.26)\,(1.212) + (0.46)\,(-1.04)}{1.72} = 0.61\,\text{RPM}$$

The reason for the increase is that 88 decibels is more 'low than 'high', so the result was more to 'increase the speed than 'decrease it.

How these two fuzzy rules interact with each other to control mill speed changes for any value of sound is shown in Figure 7.

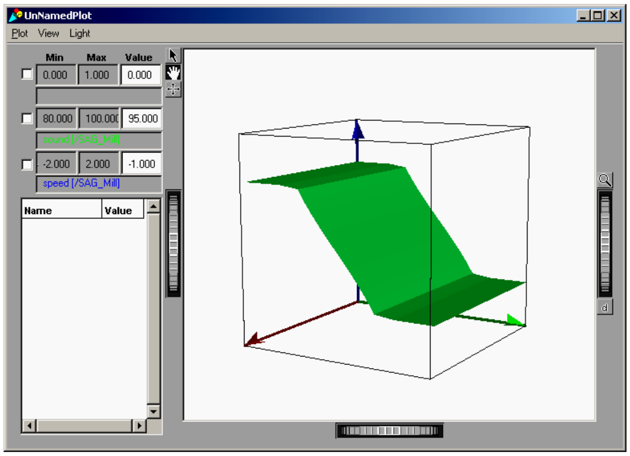


Figure 7. 3D plot of how mill speed is changed according to the two fuzzy rules that consider the fuzzy values of sound

With the basics of fuzzy control and mathematics defined we can now review how the feed to the Sag mill might be specified in fuzzy rules.

EXAMPLE OF FUZZY SAG CONTROL SYSTEM

The following examples show how the feed rate to a mill can be controlled using fuzzy logic.

FEED CONTROL RULES

Controlling the feed rate to a SAG mill is at the heart of all grinding optimization systems. Besides trying to maximize the tonnage rate it is necessary that constraining elements also be monitored and used in the determination of optimum federate. For example when the mill weight (bearing pressure) is near its high limit or is increasing rapidly, then the feed should be decreased in order to avoid overloading the mill. Likewise, if the weight is low, then the feed should be increased.

The following figure shows how such fuzzy rules would appear in the KnowledgeScape™ system. In this case, there are four fuzzy rules operating simultaneously.

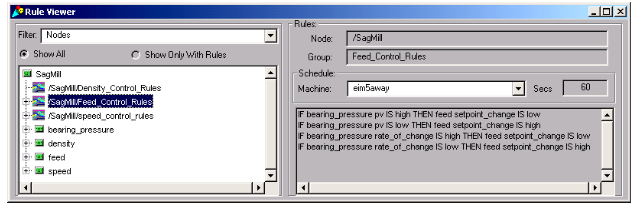


Figure 8. Fuzzy Sag mill federate rules

SPEED CONTROL RULES

In general, a high speed is preferred since more grinding occurs when the rocks experience more and harder impacts. However, a high speed may throw grinding balls too far so as to impact the liner and not rock, thereby increasing liner wear. These ball-on-liner impacts cause a lot of noise, so sound is often used to control the mill speed. Besides sound, the mill bearing pressure can also be used to control the mill speed. If the mill weight is increasing, then an increase in mill speed will help grind more rock. If the mill weight is dropping very quickly, then the speed should be decreased so as to maintain process stability.

In general, either sound or bearing pressure can be used because of the tendency for the sound to increase when the bearing pressure is decreasing.

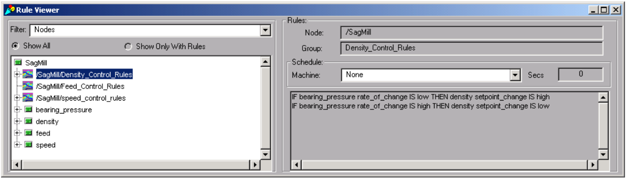
MILL DENSITY CONTROL RULES

The feed water addition to Sag mills is also a very important control variable. There are many approaches that can be used in controlling the water. One way is to use the steady state equation for density in the mill which is shown in the following equation.

$$Density = \frac{Rock\,[tons/hour]}{Rock\,[tons/hour] + Water\,[tons/hour]}$$

The fuzzy rules for controlling density as a function of how quickly the bearing pressure is changing are shown in Figure 9.

Figure 9. Example of fuzzy mill density rules



RESULTS

During the past 15 years we have reported on numerous occasions that expert control of grinding circuits and specifically Sag mill circuits results in increases in throughput rates of 4 to 8 percent. We have often times seen improvements beyond 8 percent but rarely get permission to report these higher improvements. Figure 10 below shows two histograms comparing Sag mill throughput rates when the mill was being run by operators through the distributed control system and the same circuit being controlled by a fuzzy expert system using the concepts discussed in this paper.

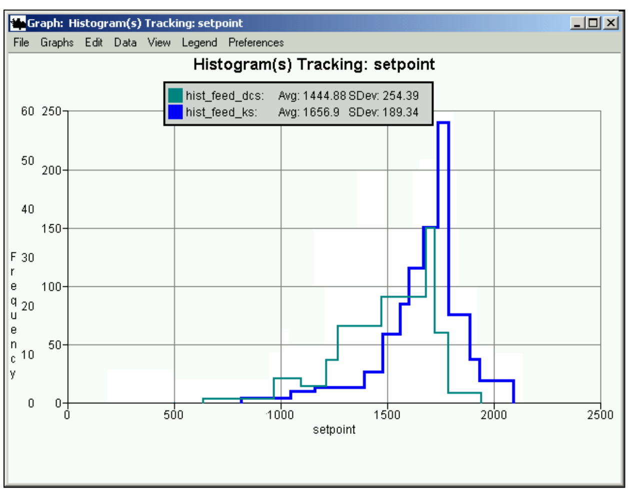


Figure 10. Comparison of Fuzzy Expert Control Results and Operator/DCS Control

The results shown in the figure are very representative, in that the expert strategy increases the throughput rate while decreasing the standard deviation of the tonnage rate. In this case a 15 percent increase in throughput rate was achieved which is at the high end of performance increases we have accomplished in our many expert control installations.

In addition to the obvious advantage of a 15 percent increase in throughput rate fuzzy expert systems offers many other advantages over both operator control and traditional expert control systems. Some of these are:

1. Control System Tuning- Increasing or decreasing the response to a particular input variable is as simple as shifting a conditional fuzzy shape. Changing the limits of the response are as easy as shifting the conclusion fuzzy sets.
2. Understanding how the rules operate is easy because they are in English. The statement ‘If sound is high’ is much easier to understand than the equivalent statement in a DCS language. Even people not familiar with the particular dynamics of the mill can still understand the fuzzy logic.
3. The rules can be printed out, documented and evaluated more easily than equivalent rules in DCS. New employees can read the rules to understand the process. The fuzzy rules can serve as a training manual.
4. The rules help eliminate the variances that exist between operators. The best characteristics of one operator can be combined with the best characteristics of another into a uniform ‘code of conduct.’ This reduction improves overall quality, and may reduce personal conflicts.
5. It is easier to experiment with new control ideas. If a totally new situation arises, then the operator only needs to create a couple of new fuzzy sets and assign a few rules. Because of the simplicity of fuzzy logic, more complex ideas can be implemented in a cost-effective manner. These tweaks fundamentally demonstrate the

increased value of fuzzy logic. Fuzzy logic improves the bottom line.

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