Benefits Analysis of Implemented Supervisory Control Systems

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Abstract

Benefits analysis of an adaptive optimizing expert control system installed and operating at a U.S gold and a South African precious metal producing concentrator are studied. Plant historical data are compared with performance data under operator control after implementation of the adaptive optimizing control system. These are, in turn, compared with performance data using the adaptive optimizing control system. Proper statistical tools and analysis techniques are discussed. Technical and practical pitfalls of performance comparisons are also presented. These pitfalls are illustrated from data published in the literature. Pros and cons of a "Pay For Performance" approach are reviewed.

Introduction

The implementation of adaptive optimizing control systems brings with it the expectation of improvements in process performance and controllability. Specifically, expectations include a shift in the mean value of the gross measure of process performance, and/or a decrease in process variability. For continuous processing operations, these expectations generally equate to increased production, improved product quality or reduced operating cost along with improved process stability.

Furthermore, benefits analysis for advanced control systems is necessary for many reasons including:

- To justify the dollars spent in implementation
- To justify the continued use or cost of further improvement of the advanced control system
- To illustrate the large value and impact of the small improvements (1 to 10%) made by the system
- To accurately assess the impact of the advanced control on the process as the small but highly profitable improvements are generally impossible for the observer to discern by watching minute by minute control of the plant

When analyzing noisy data, the changes in the descriptive statistics may be difficult to visualize and/or quantify. Thus, statistical methods and sound engineering must be employed to determine if there are significant performance differences between operations with and without advanced controls. Differences in mean values can be verified, to a specified level of confidence, using hypothesis testing and calculation of the standard T-statistic. Similar comparisons for the width of distributions can be accomplished using a chi-squared test.

Source data used in these tests and comparisons must be carefully gathered and analyzed. The possibility exists to compare performance data that yields results that appear to support findings that are unwarranted. This is the rationale behind using sound engineering principles to gather and process the data before generating comparisons and concluding results. It is often natural in processing plants with parallel production circuits to infer conclusions during side-by-side operations. Although these comparisons are sometimes warranted, often conclusions are generally reached without regard or compensation for the biases that usually exist between parallel processing circuits. These types of data can be compared using a more careful and more detailed use of statistical testing procedures and more involved analysis of data.

Several humanistic complications may arise in attempting to properly analyze the benefits from implementation of advanced control. Furthermore, these may be of a magnitude to override the benefits derived from performing the analysis. These will be discussed in detail the body of the paper. These non-technical concerns illustrate the need to keep focused on the ultimate objective of the project, which is to "**successfully** implement a control strategy that improves process profitability". The best control strategy in the world produces no benefit if it is not used. Complete buy in and support from plant personnel is absolutely essential to the ultimate success of the project.

The issues and procedures discussed in this paper should provide the industry a basis for making performance comparisons that can withstand the scrutiny and examinations of even the most rigorous analysts and satisfy the needs of the end user.

Data Collection Procedures

A defensible comparison of the descriptive statistics for process performance with and without advanced control requires that testing be performed under comparable process conditions. In other words, all of the conditions that influence process performance should be included in the time that the process is operated with and without the advanced control system. This is the underlying assumption in making the comparison. This is the reason why parallel line comparison is not a valid way to compare results outside of equipment comparison. That is, intrinsic in the use of parallel processing lines is the fact that the equipment (which produces the results to be compared) is absolutely different. The differences may be minor or major, but they are uncontrollable and undefined. Therefore, the assumption that all conditions that effect process performance, except for the use of advanced control (the test parameter) are equal is almost certainly false. Therefore, the assumption of equal test conditions for evaluating the advanced control strategy is only valid for comparing data on the same process line. Once the comparison is made on the same line, additional potential differences must be taken into account for the following performance-affecting parameters:

- raw materials characteristics and quality
- time variant responsiveness of the process
- plant operations personnel and operating philosophies
- processing circuit configuration

- process interruptions due to external influences such as maintenance, scheduled shut downs, or forced shut downs due to upstream or downstream constraints

These differences are properly handled by gathering a sufficient number of data points for comparison and /or randomizing start time and length of the "on/off" test periods. Data evaluation may also be simplified by excluding data that is not relevant such as:

- data gathered during a process shutdown or
- data gathered from a sensor that is out of range or out of calibration

The exclusion of "bad" data points may be performed with data filters and should be carefully thought out to avoid exclusion of "good" data which may bias the results. As the number of data points increases, the statistical confidence also increases. Relevant and detailed data with time-stamps must be sampled and recorded at appropriate intervals for all process variables and control variables that indicate process performance. Reduction and evaluation of the data can be further simplified when uniform time increments are used throughout testing.

Historical data may be used for comparison of the benefit of implementing an advanced control strategy, however, as this data collection is unstructured, a larger population of data points is necessary in order to equalize the potential effect of performance affecting parameters and achieve statistical confidence.

A quicker, but equally valid data collection approach involves a comprehensive on/off test campaign. During an on/off test campaign, the process is operated for random periods under one type of control and then under another type of control. The entire test campaign must include enough time that there is reasonable confidence that both the on periods and off periods contain equivalent contributions of dependencies and bias'.

On/Off Test Procedure

The on/off test procedure is a means to sample and quantify the process performance under different operating conditions or control strategies. The process is operated under one set of conditions or control strategy and then it is operated under another set of conditions or control strategy. The on/off test procedure is sometimes mistaken to be a bi-modal testing procedure; meaning that it tests two different types of operation or control strategies. However, the on/off test procedure can be extended to include multiple operating conditions or control strategies. As the number of different operating conditions or control strategies increases, the time required to perform the entire procedure increases rapidly.

The on/off periods should be long enough to ensure that measures of performance accurately represent typical performance of the process. When practical, the on/off periods should exceed three times the longest expected settling time of a process disturbance. This allows for disturbances in the process to cascade entirely through the process and thereby recording the response of the control strategy to the disturbance. It is also a means of normalizing the effects of process disturbances in the process data being sampled in the circuit.

Data collection should be discontinued for three times the longest expected settling time of a process disturbance when switching between the test conditions so that switching between the test conditions does not bias the data. For example, the process should be run without data collection for one hour, if 20 minutes are required to recover from the longest expected process disturbance. Process disturbances include process setpoint changes or unmeasured disturbances in process raw materials. Failure to compensate for the effect of switching between test conditions will yield a "conservative" comparison as the data will tend to benefit the condition the achieved the lower performance rather than benefit the condition that yielded the superior performance.

Assuming that process disturbances are distributed normally, random test periods distributed over a sufficiently long period will compensate for bias' included in the process data due to unmeasured process disturbances or testing error. The test periods should be scheduled with care so as to prevent alignment with plant operations personnel changes or bias' that might result in the process data. This last requirement requires some judgement and intuition.

The on/off test schedule should be randomized and a schedule for testing should be generated. Minimum and maximum time periods for each test condition should span the expected time period between process disturbances. The total testing period should extend several weeks or months depending on the variations and disturbances of the process raw materials. An example of a two week "on/off' test campaign schedule is shown below.

Random on-off Sequencing				Start Date: 6/10/98		
Minimum Segment: 6		Maximum Segment: 14		Start Time: 18:00		
On(1) or Off(0)	Number of Hours	Cumulative Hrs On	Cumulative Hrs Off	Date	Switch Time:	Days
0	0	0	0		6:00 PM	0
1	6	6	0		12:00 AM	0
1	13	19	0		1:00 PM	1
0	7	19	7		8:00 PM	1
1	9	28	7		5:00 AM	1
1	12	40	7		5:00 PM	2
0	6	40	13		11:00 PM	2
1	7	47	13		6:00 AM	3
1	8	55	13		2:00 PM	3
0	8	55	21		10:00 PM	3
0	7	55	28		5:00 AM	3
0	10	55	38		3:00 PM	4
1	11	66	38		2:00 AM	4
1	8	74	38		10:00 AM	5
1	9	83	38		7:00 PM	5
0	13	83	51		8:00 AM	6
0	9	83	60		5:00 PM	6
0	7	83	67		12:00 AM	6
1	7	90	67		7:00 AM	7
1	13	103	67		8:00 PM	7
0	7	103	74		3:00 AM	7
1	8	111	74		11:00 AM	8
0	12	111	86		11:00 PM	8
0	12	111	98		11:00 AM	9
0	9	111	107		8:00 PM	9
1	11	122	107		7:00 AM	10
0	8	122	115		3:00 PM	10
0	7	122	122		10:00 PM	10
0	6	122	128		4:00 AM	10
0	7	122	135		11:00 AM	11
1	12	134	135		11:00 PM	11
0	13	134	148		12:00 PM	12
0	11	134	159		11:00 PM	12
1	10	144	159		9:00 AM	13
0	7	144	166		4:00 PM	13
1	13	157	166		5:00 AM	13
HOURS	323 TOTAL	157 ON	166 OFF			

Figure 1 – two week “On/Off” test campaign example

Data Evaluation

Rigorous treatment of the data can be accomplished using the principles of design of experiments (DOE), as outlined by Box, et al. (1). The assumptions that for the basis of DOE include a requirement that the parameters of interest are independent. This is rarely the case in processing plants. For example, a variation in the process-train configuration may be necessitated by the physical or chemical properties of a particular feed stock. Consequently, there is an inherent dependence between those parameters that may bias the statistical treatment of data.

The proper statistical tools for comparing the process performance under advanced control or operator control are the mean value and the standard deviation. Statistical comparison of means allows the user to objectively determine the benefit associated with a type of control. The comparison of standard deviations allows the user to assess the stability or consistency of either type of control. Due to the different nature of each process, the absolute standard deviation means little in this comparison, whereas the relative standard deviation is significant. Graphically, a histogram is a valuable tool for illustrating the differences between control strategies and is readily understood by the viewer. Also, histograms provide a powerful tool for storing information about the process data without increasing the amount of data that is stored. This is due to the fact that histograms simply store the frequency of occurrence of a number rather than storing the raw number. The mean and standard deviation may even be estimated based solely on the histogram data. The accuracy of this estimation depends on the resolution of the histogram bins and the number of data points collected.

Analysis of the data can is usually easy by separating the data for the on condition into computer files and data for the off condition into computer files. The data for each test condition can be classified or sorted into value bins to produce histograms for visualization of the data. Additionally, the mean value and standard deviation of the data for each on and off condition are calculated.

The null hypothesis is that the mean values of each data element corresponding to the on and the off conditions are equal. This can be expressed mathematically using the following notation:

$$\mu_{on} = \mu_{off}$$

In this equation μ represents the true mean value for the data element. But because the true mean is unknown, the calculated mean value is used and the t statistic is calculated using the following equations:

$$t = \frac{\overline{X}_{on} - \overline{X}_{off}}{SE_{dif}}$$

$$SE_{dif} = S_{pooled}\sqrt{\left(\frac{1}{n_{on}} + \frac{1}{n_{off}}\right)}$$

$$S_{pooled} = \sqrt{\left(\frac{(n_{on} - 1)^2 s_{on}^2 + (n_{off} - 1)^2 s_{off}^2}{(n_{on} + n_{off} - 2)} \right)}$$

$$s_k^2 = \frac{\sum_{i=1}^{n_k} \left(x_i - \overline{X}_k \right)^2}{n_k - 1}, k = 1(on), 2(off)$$

The t statistic then compared with values taken from the t distribution at the appropriate confidence level and degrees of freedom. If the computed value for the t statistic exceeds the tabulated value, then the two means are significantly different and the null hypothesis is rejected.

The data analysis presumes accurate representations of the performance of the two systems. Care must be taken in how data are recorded to use in the analysis. If the data corresponding to the time required to ramp up or down to the actual average performance of the test conditions are included in the performance measure for that strategy, the result could be biased toward the test conditions that perform more poorly. This results in the results of the better performing test conditions to appear to be closer to the poor performing test conditions. When these effects become significant, a comparison between the calculated t statistic could result in the null hypothesis being accepted when a significant difference really exists in the data for each test condition.

Pitfalls

The greatest pitfalls in comparing advanced control strategies are:

1. attempting to compare data on parallel processing lines
2. attempting to draw conclusions with insufficient data points
3. tracking the wrong data
4. operator limitation of the strategy

As previously mentioned parallel line comparison is invalid for control strategy comparison because it fails the basic logic test of identical equipment conditions. This is precisely why parallel line comparisons are used to differentiate between equipment.

The second issue is more difficult because it is not a black or white situation. In general, the more data you have the better the confidence you have in the conclusions. Practically, it is desirable to have roughly the same number of points (and a sufficient quantity) with the control strategy in question on or off. If 80 or 90% of the points are taken with control on or control off, the results will be biased. One of the reasons for this is insufficient data; however, the other reasons have to do with why there is an inequity in the run time. If the strategy is off mostly, it may only be turned on when operating conditions are favorable. If it is mostly on, the small amount of "off" times may indicate process problems that the strategy could not handle and therefore the operator took the strategy offline. In either extreme, the data suggests problems that may bias the data one way or the other.

The third pitfall involves what data is tracked during the analysis. For example, the tester may be tracking the process setpoints he is controlling, however the process value that results may be very different from the nominal setpoint depending on loop tuning and the controller mode. If the controller is placed in manual, then the setpoint means absolutely nothing. For this reason, the user must be wary of what values he/she is tracking.

The fourth pitfall involves the degree to which the operator can influence or limit the control strategy. Operators are frequently given the ability to set limits or targets for a control strategy in an effort to get “buy in”. However, if operators are given the ability to limit the control strategy from achieving its goals then the control strategy comparison will also yield inaccurate results. The operator may have this effect on the control strategy by setting lower targets or constraining manipulated variable limits so that the control strategy cannot achieve its full benefit. The solution to this problem is to minimize the critical parameters that the operator can adjust and to track the occurrence of process limiting conditions. Minimizing the parameters that the operator can adjust is the real solution, but where he must be given access to control limits, the system integrator can, at least, justify the results achieved based on the percent of the time the strategy was limited from fulfilling its potential.

Practical Aspects of Benefits Analysis

Aside from the technical issues of correctly staging the comparison, gathering data and statistically evaluating it, there are socio-political issues with performing a benefits analysis. While data should always be collected and evaluated, how the comparison is made may have dire consequences to the success of the project.

Operator Learning

One difficulty in making valid comparisons between human control and programmed advanced control is the fact that humans learn with time. That is, when advanced control is first implemented at a plant, the operator observes what decisions the system is making and modifies his or her behavior to emulate what he or she determines to be good response. This phenomenon has been observed in other industries also. For example, stock brokerages began using Expert systems several years ago to improve their investment decision making. Initially, it was found that the stockbrokers relied heavily on the Expert system. However, with time, it was discovered that the stockbrokers used the Expert system less and less to aid them in decision making. When queried about this, the stock brokers indicated that they did not use the system any more because they had learned how it made decisions and had incorporated those techniques in their own decision making strategies. Therefore, even though the Expert system was not being heavily used, it had achieved its purpose in improving the decision-making strategies. Because humans learn by exposure, it is virtually impossible to get a valid “blind” comparison between the system and the human operator. This comparison is most valid at the beginning of the implementation when the human operator has had less time to learn and modify his/her behavior. One way to improve this comparison is to gather data prior to implementation and use this as a base line for comparison.

Operator Competition

Whenever an "On/Off" testing campaign is undertaken, it is very difficult to perform without it being taken by the operators as a competition. This is particularly the case in "pay-for-performance" projects where money is at stake for both the system integrator and the end-user. This type of Us vs. Them competitive atmosphere is highly destructive to the success of the project. Once the testing becomes viewed as a competition, operators change their normal techniques for controlling the process and make the comparison quite difficult. Also, if there is a strong "ego" to the operators or if it becomes a matter of pride, the operators have strong motivation to manipulate the process to their advantage. These reactions, in turn, polarize the operations staff and the system integrator who is motivated to earn the "buy-out" for the system and defend the control strategy he/she has created. This lack of trust requires even greater attention to how the data is gathered and interpreted and casts doubts on the results.

However, most importantly, even if a substantial benefit is documented, the wall of mistrust that has been created during the testing between the operations staff and the system integrator remains and there is no "buy-in" by the people who are responsible to run the strategy. Even with extensive training, discussion and socializing, it may be impossible to undo the damage caused by the competitive atmosphere formed during the test. If this cannot be reversed, then the end user gets a technically superior advanced control system that produces no benefit as the operators refuse to use it or limit its control.

Because an "On/Off" testing campaign may be construed as a "competition", it violates one of the best practices of advanced control system implementation – the "team" approach. For all of the above reasons, the end user as well as the system integrator should be cautious about how data is to be gathered and assess the relative importance of the data vs. the potential alienation of the operations staff and formulate as not competitive an approach as possible. Doing so, may be the most critical action in the successful implementation of advanced process control.

U.S. Gold Production Benefits Analysis Example

The following data analysis example is from a Western U.S. Gold producer using KnowledgeScape to maximize production through the grinding circuit. The data from the KnowledgeScape database reports was analyzed according to the above-prescribed procedures. The daily reports were imported in to an Excel spreadsheet and combined in to a continuous table for the entire test.

The first hour of each test period was removed from the data to eliminate ramp-up or ramp-down. The data were adjusted for incidental mill down time that affected the throughput average tons per hour. Mill down time caused by expert system errors or operator errors was not eliminated from the data so that accurate penalties could be given for poor performance. The data were also analyzed to eliminate anomalous readings due to signal or equipment failure.

Histograms and calculated averages of throughput (tons per hour), grind size (%-200) and SAG mill power usage were generated from operator, expert rules, and optimizer control for performance comparison. Other parameters such as mill loading, set point limiting, and emergency status that indicate efficiencies and constancy of performance were calculated and reported as well. Figure 2 is a histogram plot of throughput comparing operator and expert control. Figure 3 is a histogram plot of throughput comparing expert rules and optimizer control. Figure 4 is a report summary of the mill parameters recorded during the performance tests.

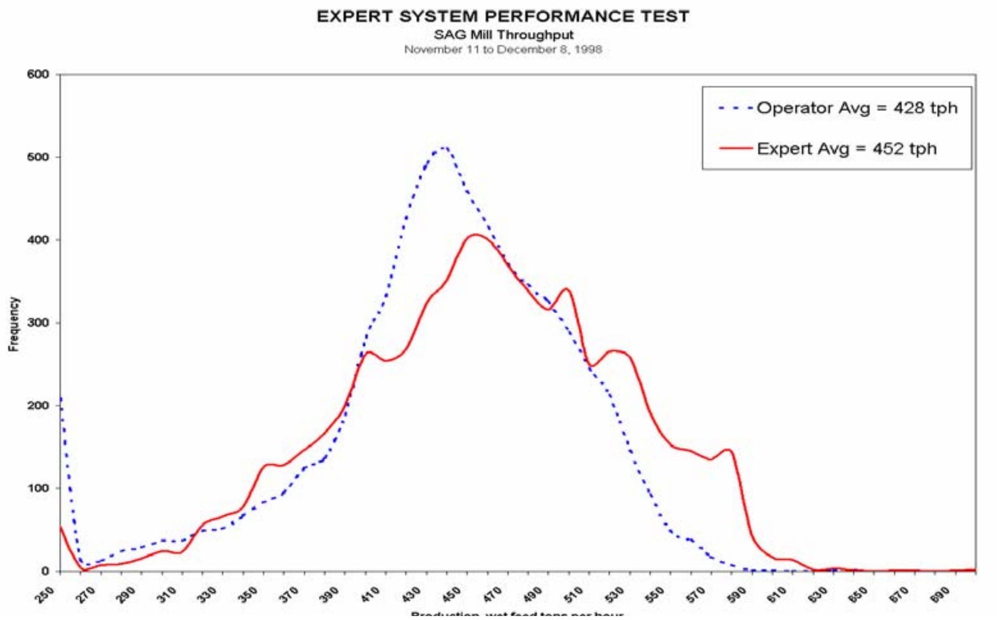


Figure 2 – Histogram Plot of Mill Throughput for Operator and Expert Test Periods

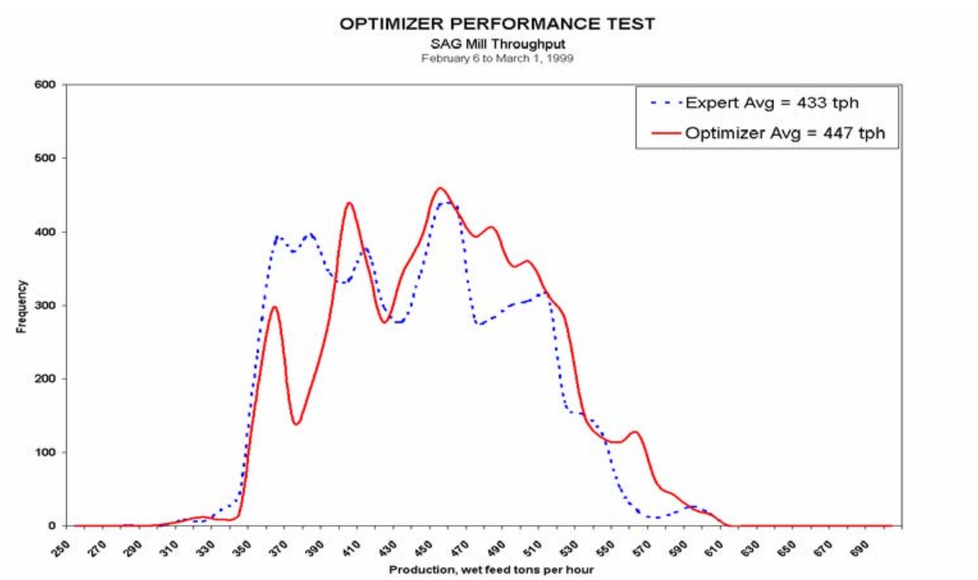


Figure 3– Histogram Plot of Mill Throughput for Expert and Optimizer Test Periods

Figure 4- Optimizer Test Results

	Optimizer ON	**Optimizer OFF**	**Benefit**
Total Test Time, hrs	219.8	212.7	
Avg. Tons/hr	447	433	**3.3%**
Avg. Power, hp	2218	2,054	
Avg. Image Size	0.097	0.095	
Avg. Grind Size, %-200	65.7	65.4	0.4%
Avg. Density, % solids	42.5	41.7	1.8%
KW/Ton	4.96	4.75	4.5%
Ball Mill Overload	36%	44%	-17%
Feed Limited	44%	32%	36%
Optimizing Ball Mill	51%		
Optimizing SAG Mill	20%		
Unlimited Feed tph	427	386	**10.6%**

After startup, and commissioning, the system was put through lengthy evaluation tests to determine its effectiveness in meeting the plant goals of increased throughput at consistent grind size. Expert control was tested vs. operator control, and then optimizer control was tested vs. expert control.

During the testing it was observed that the ball mill was the limiting factor to SAG mill throughput up to 80% of the time, but during the first test, the expert rules were able to keep the grinding circuit loaded as much as possible. During the second testing period, the optimizer kept the circuit loaded as well but was able to increase throughput under ball mill limited conditions by improved grinding efficiency in the SAG mill.

The expert rules increased total throughput 5.6% over operator control while maintaining the same power efficiency. When the optimizers were tested against the expert system, the overall realized increase in throughput due to the optimizers was 3.3%. These values are additive giving a comparative value approaching 9% increase in throughput when using the expert rules with optimizers vs. normal operator control.

<u>Precious Metal Production Benefits Analysis Example</u>

The following data is presented based on a brief 88 hour preliminary “On/off” test conducted on a Sag mill Expert control strategy located in a precious metal concentrator. While the time is too short to derive high confidence, the margin of improvement is sufficient to confidently conclude that plant tonnage significantly increased and variance in the key process indicators decreased (more consistent operation) under Expert control.

Microsoft Excel - Amandebult Performance.xls

On/Off Data Analysis

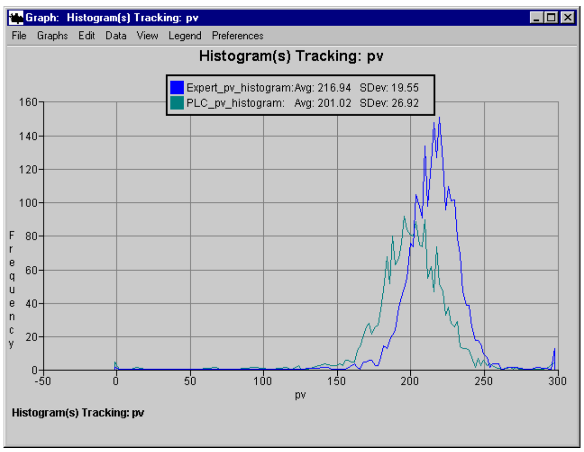
Client		
Plant		
Circuit	SAG Mill	
Comparison Hours On	50	61%
Comparison Hours Off	32	39%
Comparison Total Hours	82	100%
Start Date	25-Mar	
Start Time	14:00	
End Date	28-Mar	
End Time	AM (midnigh	
Feed Ltd Counts	1007	89.9%
Speed Ltd Counts	0	0.0%
Water Ltd Counts	67	6.0%
Coarse Particle Size Counts	471	42.1%
Pebble Particle Size Counts	198	17.7%
Fine Particle Size Counts	0	0.0%
Emergency Counts	4	0.4%
Optimizing Counts	447	39.9%
Total	1120.0	100%

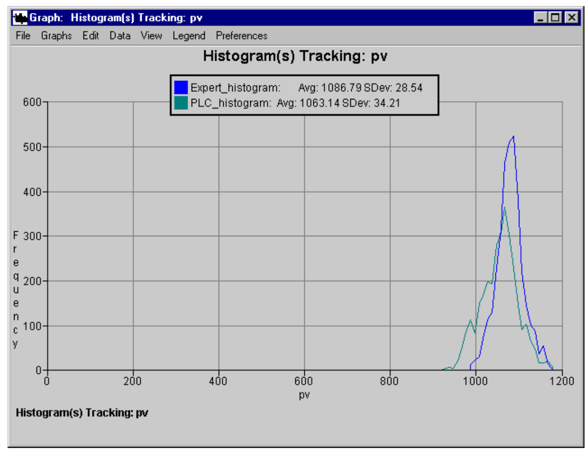
SUMMARY STATISTICS

Statistic	Units	On	Off	Delta	% Change	SDEV On	SDEV Off
Feedrate	MTPH	216.94	201.02	15.92	7.92	19.55	26.92
Mill Load	MT	98.33	86.29	12.04	13.95	7.54	11.02
Power	KW	1086	1063.14	22.86	2.15	28.54	34.21
Speed	% Crit RPM	75.05	74.21	0.84	1.13	4.85	4.65
Water	% Ratio	42.34	44.91	-2.57	-5.72	4.95	6.81
Mill Disch Density	MT/M3	1.59	1.58	0.01	0.63	NA	NA
Flot Feed Density	MT/M3	NA	1.63	NA	NA	NA	NA
PSM	%-106 um	NA	49	NA	NA	NA	NA

Date	Start Time	Stop Time	On Duration	Off Duration
25-Mar	14:00	22:00	8	
26-Mar	14:15			16
27-Mar				
28-Mar		6:15	40	
	8:15	10:15	2	2
29-Mar	1:00	END		15
	Midnight	Total	50	33
		%	60%	40%

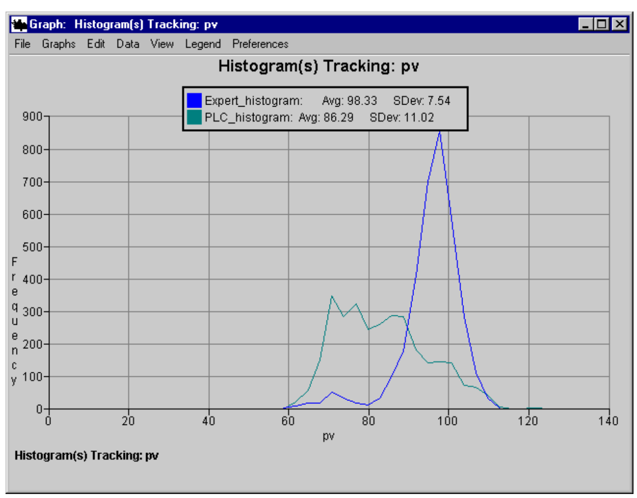
Summary / 3-25-99 / 3-26-99 / 3-27-99 / 3-28-99





Mill Feed Rate (MTPH) **Mill Load (MT)**

This data clearly shows an improvement in process tonnage of over 8% despite being feed rate limited almost 90% of the time, with an associated increase in mill filling of almost 14%. Power increased 2.14%, however KW/MT decreased from 5.3 to 5.0 as the mill ground more efficiently.



Mill Power (KW)

Improper Data Interpretation Example

The following example was taken from published material. A well-known company in Expert system implementation, company X, was called in to revamp grinding control at a major copper concentrator. Previous to company X's involvement, another Expert system integrator, company Y, had designed and installed a grinding control Expert system at the plant. Company Y had correctly gathered data, analyzed the data to compare means and standard deviations and presented its findings to plant management on several occasions over a 1.5 year implementation period. Results for the multi-grinding line plant varied from 3.4% to 6.9% over different testing periods. Initial data had been generated from an official "on/off" testing program. Subsequent data came from normal plant operation practice comparing results when the strategy was turned on vs. when it was off. An example of the histogram data collected and presented by company Y during its implementation is shown below.

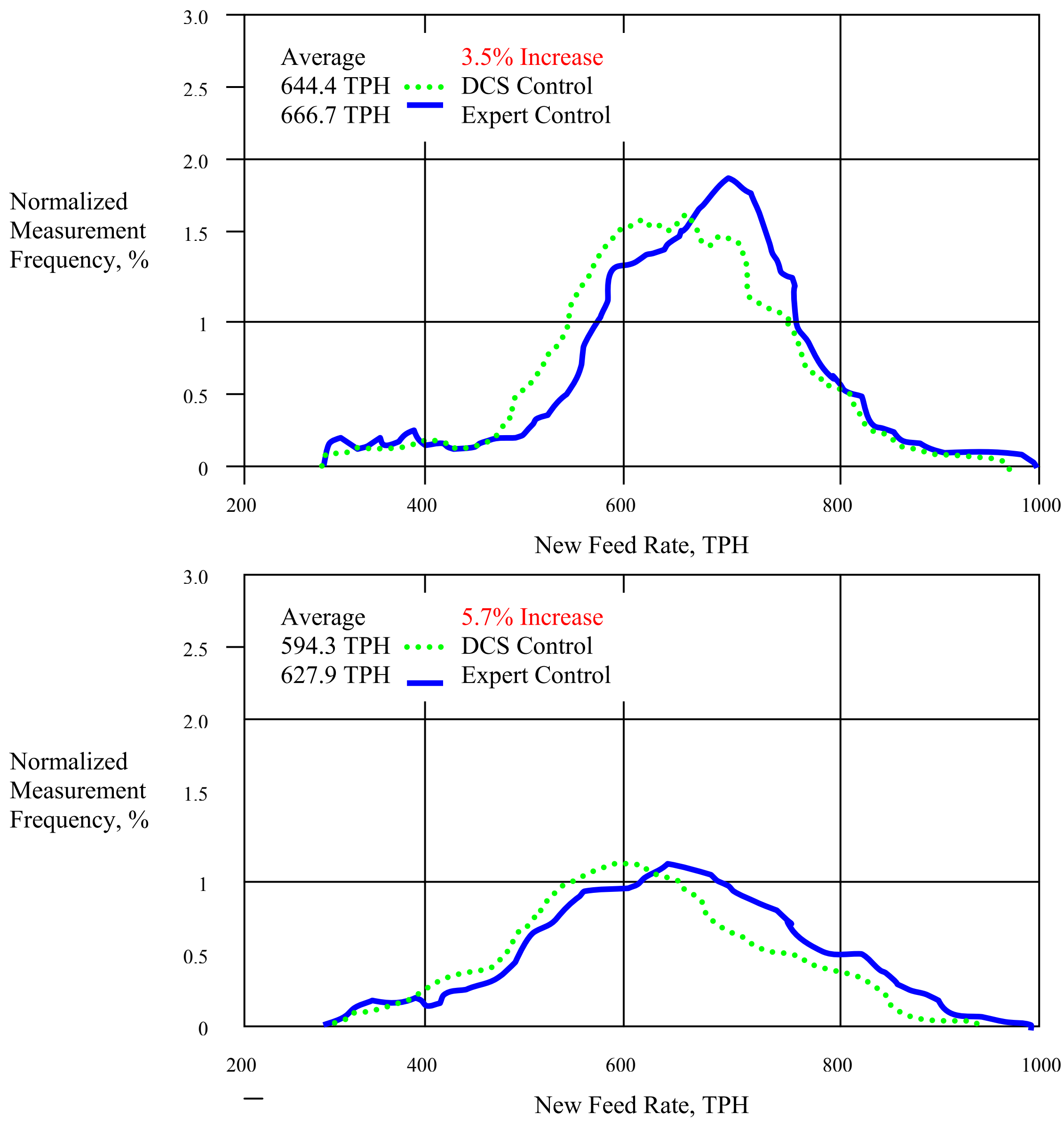


Figure 5 – Typical Histograms of Mill feed rate with and without Expert control

Despite the presentation of superior technical performance documented using good statistical tools, management was not satisfied with the overall project. This was primarily due to lack of 'buy in" and support by one or more of the operations crews. Due to the lack of operator satisfaction, the project dwindled until it was described as a "failure". At this point, plant management, unable to get sufficient attention from company Y, called upon company X to revamp the grinding control. Company X began its project with the plant and after several months and many changes to the existing control, plant management declared that it was satisfied. One of the major reasons for management's satisfaction was that comments from the operators indicated their satisfaction with the new Expert control strategy and their "buy in" to it. Company X and plant management attempted to quantify the benefit and determined that the control strategy that was working on one of the grinding lines had produced a 20 to 30 TPH improvement. The evidence cited was that the grinding line upon which the Expert control was operating was averaging approximately 2.7% higher than the adjacent grinding lines. As it neared the end of the project, Company X decided to perform a proper "on/off" comparison. The data from the one grinding line that the strategy had been implemented on, was analyzed to determine the average feed rate improvement with Expert control turned on vs. turned off. The results of this analysis indicated that with Expert control on, this grinding line achieved an average of 764.1 TPH compared with 761.1 TPH without Expert control. This difference of 3.0 TPH represents a 0.39% actual improvement instead of the erroneously interpreted 2.7% (20 to 30 TPH) improvement.

Despite the fact that the results using the Expert control strategy implemented by company Y had yielded statistically valid and documented improvements of 3.4% to 6.9% while the statistically valid results from company X's Expert system were only 0.39%, the Expert system of company X was advertised by both plant management and company X as a great success compared with company Y's "failed" attempt. Besides the technical results, operator satisfaction with the company X Expert system was touted as the greatest benefit. In retrospect, once the real improvement of only 0.39% is understood, operator satisfaction is very understandable. That is, the operators were given an Expert system by company X that did exactly what they wanted, but did not push the plant, therefore their lives were much easier than when they had run the Expert system by company Y that had pushed plant performance and generated real tonnage improvements.

This example serves to indicate the dangers of misinterpreting data and the wrong conclusions that can be derived therefrom. Poor data analysis can make a failure into a success or visa versa.

Conclusions

Proper statistical data gathering and analysis are critical to evaluation of Expert system performance in order to justify previous and continued spending. The techniques for gathering this data such as "On/off" testing programs can be easily performed, however, if a competitive or "antagonistic" environment is generated, the damage to the overall project may be overwhelming. The statistical tools of means, standard deviations and histograms best fit the data analysis for control strategy comparison. These tools provide an objective technique for comparing strategies and quantifying highly profitable yet incrementally small differences in performance that are impossible to determine through direct observation. Improper data analysis can mislead the user into drawing false conclusions and the results are associated with those conclusions.