Statistical process control of digester permanganate and kappa numbers: closing the loop with SPC

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Optimizing pulp mill throughput and production cost is dependent on the level of variation that must be accommodated in the choices of process operating targets throughout the mill. Much of the variation that occurs in the final products and by-products of the pulping operation is caused by parameters that are not under direct regulatory control, either by combinations of events that are not obvious or by over- and under-adjustment of the process. This is often true in the case of the control of the degree of delignification taking place in a pulp digester, as measured by the pulp permanganate and kappa numbers.

Mathematical techniques are available to allow statistical characterization of this variation, and the results may be used for two purposes:

1. Minimizing total variation in digester permanganate and kappa number by actuating control only when it is statistically justified
2. Providing some insight into the causes of the variation in digester permanganate and kappa numbers, allowing the magnitude of the variation to be reduced or the source to be eliminated.

The application of these principles provides the possibility of a better degree of control than may be obtained through conventional methods, as well as a tool for continuous reduction in process variation and a corresponding increase in product uniformity.

Background

The control problem

The control problem addressed here is not an unfamiliar one. The control of the degree of delignification in the kraft pulping process, as estimated by the permanganate and kappa numbers of the resulting pulp, has been the target of many strategies over the last 25 years. The following factors make the control problem a difficult one:

- The tests for permanganate and kappa numbers have significant inherent error since the size of the sample is very small compared to the volume of the process stream, and the pulp flow or mass being sampled is not homogeneous.
- The test procedures take an appreciable length of time to complete, even if automated, so that the test frequency is usually no more than one per hour if performed manually.
- There are often large transport lags between the location of the cooking reaction and the pulp sample point.
- Many of the key factors that affect the outcome of the pulping reaction are not measured on a continuous basis, and their interactive effects are not totally understood.

For these reasons, there is a large percentage of noise in the resulting measurements or test data. This fact causes many manual or purely model-based control systems to seriously over- or under-control the parameters used to adjust the cooking reaction. This increases, rather than decreases, the variation in the permanganate and kappa numbers of the pulp leaving the cooking operation.

Statistical process control

Statistical process control (SPC) has been successfully adopted by many areas of the manufacturing sector of North American industry over the last decade. It has been used as a means of reducing the variation in process output, allowing for decreased waste and rework and a final product of higher and more predictable quality and performance.

The most common SPC techniques, now familiar to many technical and operating personnel, are "control charts." These generally utilize the mathematical properties of the well-known Normal or Poisson frequency distributions. Simple statistical tests are performed on process or product data, and inference is employed to classify the behavior of the charted process output as either random (in control) or nonrandom (out of control). These results are usually charted versus time in a format developed by Shewhart (*1*) in the early part of the century (**Fig. 1**).

Classical SPC methodology, as developed by Deming and others (*2, 3*), employs the concept of "assignable causes." This procedure involves the identification and documentation of the root causes of nonrandom behavior of the variable being charted as the events occur. After a suitable period of operation, a "frequency of occurrence" (Pareto) analysis may be performed (**Fig. 2**). This allows isolation of the most frequently occurring "assignable

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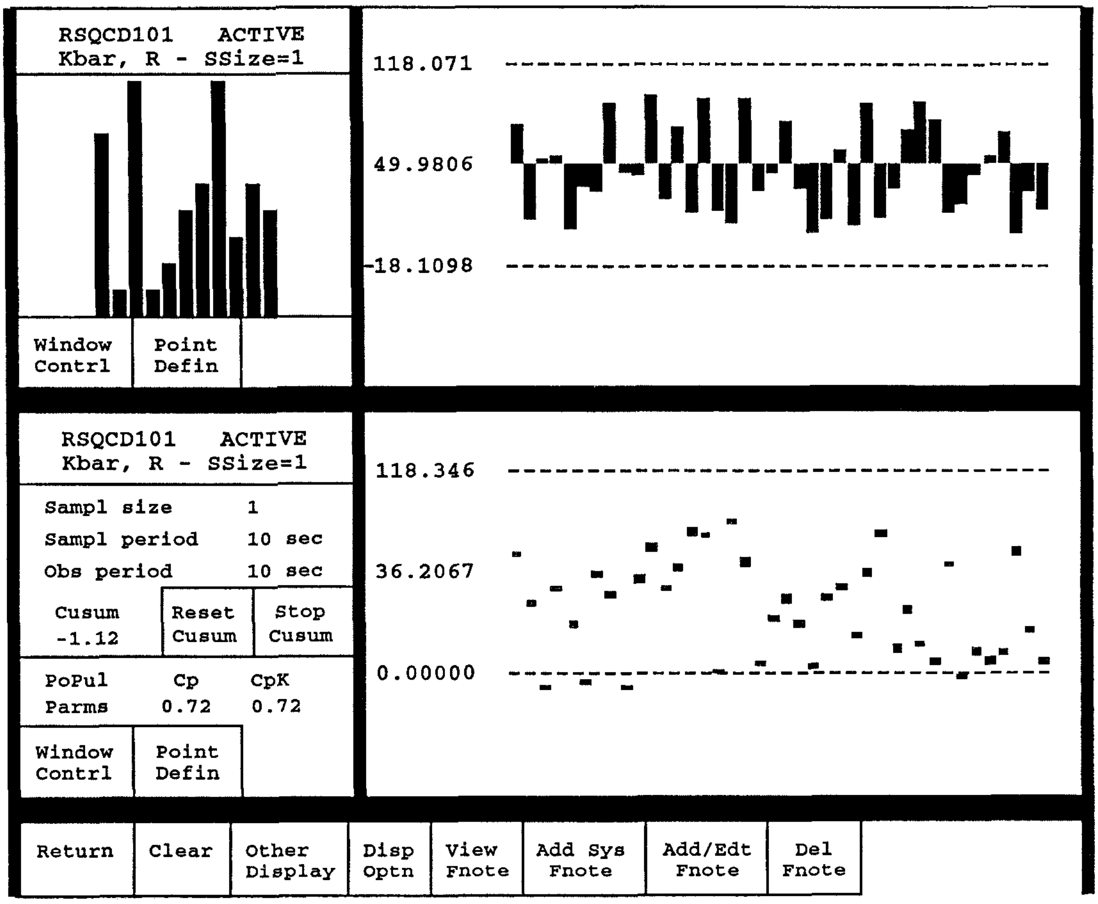
1. Typical control chart



causes" of variation, identifying possible target areas for improvement. If done properly, this is one of the most powerful aspects of the classical SPC approach.

Other techniques allow conclusions to be drawn about the "capability" of a process to produce within its manufacturing specifications. These techniques estimate the probability of the normal dispersion of the observed process data falling within specified tolerances. Various indices exist to express this capability, taking into account both the centering and width of the process distribution (**Fig. 3**).

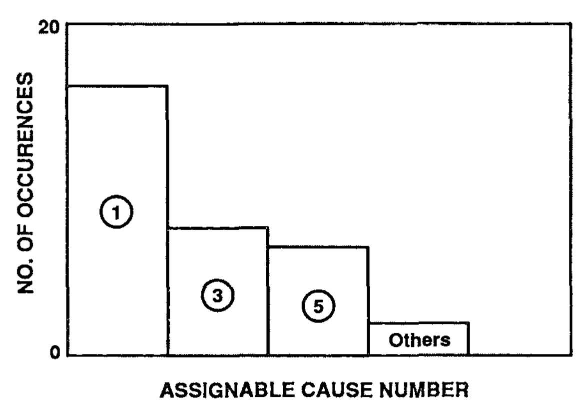
Is SPC a viable solution?

One of the key attributes of SPC is the ability to isolate changes in the normal behavior of a process, regardless of its normal noise level. The decision criteria may be selected to accurately estimate the probability of over- or under-control, thereby optimizing the process.

Another important feature is the opportunity to track the causes of statistically significant excursions or patterns in permanganate and kappa numbers so long-term improvements may be implemented.

In light of the control problems stated previously,

2. Pareto analysis of assignable causes



integration of some statistical process control components into the overall control logic for digester permanganate and kappa number control seems desirable.

Discussion

Integration of SPC and closed-loop control: an apparent clash of goals

As the manufacturing industries adopted the well-known SPC methods previously outlined, the continuous process industries were busy developing real-time, on-line process control systems. The goals of SPC were to make adjustments only when statistically valid and to track the causes of process disturbances, while the mission of the automatic control system was to minimize deviations from process setpoints regardless of the causes.

Many of these differences in philosophy arose because the cost of making an adjustment (e.g., a tooling change) is much higher in discrete manufacturing than in a continuous process where a valve might be opened or closed by an incremental amount.

These two philosophies are far apart but both have desirable qualities for permanganate and kappa number control. For instance, it would be best to have a control scheme that minimized the deviation of digester permanganate and kappa numbers from target while providing insight into the cause of disturbances. For this reason, the two approaches have been combined to provide "the best of both worlds." There were some issues that had to be addressed, however, before this combination could take place.

Problems with classical SPC: correlated data

The principles of classical SPC evolved to serve the needs of the manufacturing community. The mathematics of the majority of standard techniques relies on the subject data to be independent and close to normal in distribution. The majority of discrete processes can be made to conform to these requirements by appropriate subgrouping of the test data. This is the reason that most XBAR and R charts used in industry employ a sample subgroup size of three or more.

In continuous or semicontinuous processes, however, the patterns of variation in process variables are usually time dependent. This follows naturally from the uninterrupted nature of the process. It also poses a significant problem: unless consecutive samples are taken a very long time apart from each other, they will be certain to show some pattern, and therefore will not be statistically independent. This renders standard statistical techniques invalid and may, in many cases, lead to seriously misleading conclusions.

This phenomenon, known as self-correlation or autocorrelation, may be tested for by the use of the autocorrelation function. This test provides an estimate of the degree of self-correlation in a variable and shows how many sample periods back in time the autocorrelation remains significant. Tests on permanganate and kappa number data from many mills revealed that significant autocorrelation existed in all cases.

Figure 4 depicts the typical results of an autocorrelation test, which essentially performs a standard correlation analysis using each piece of data and the ones sequentially preceding it as matched pairs. The resulting coefficients of correlation are then plotted versus time. Note that the degree of correlation tends to decrease with time, so that samples taken far enough apart are essentially independent.

How can we deal with this?

Many studies have been performed on the treatment of autocorrelated data in the last 10 years. One method that lends itself particularly well to this application is the use of time series. There are a large number of time series available, so the selection process is important. In this case, very good success was achieved with the use of the family of time series known as "autoregressive integrated moving averages." These series were first proposed for control purposes by Box and Jenkins (*4*) in the 1970s as a means for modeling correlated data. They have been employed extensively in other fields such as economics. The use of time series models such as these allows the time patterned variation in the permanganate and kappa number variables to be tracked or estimated with a high degree of consistency. The next step is to integrate this technique into an overall control strategy.

Integration of SPC into closed-loop control

In the presence of significant noise, the minimum average error from a target may be achieved by controlling only when a statistically significant change in the noise pattern takes place. This condition was satisfied by providing a strategy that required statistical "permission" to actuate a process change.

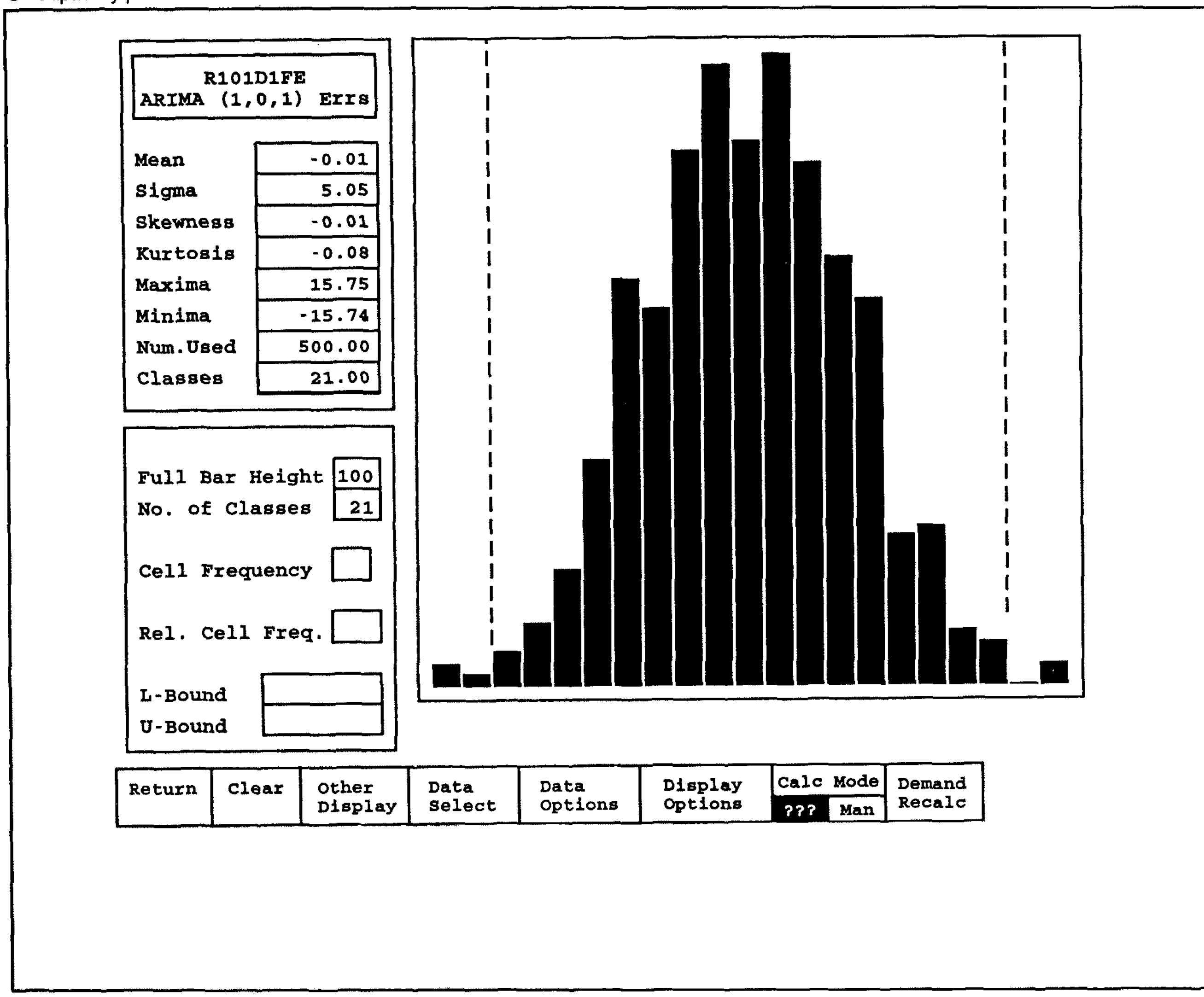
This statistical permission was calculated by analyzing the permanganate and kappa number data. The variation in this data was mathematically split into two components: the time correlated or time patterned portion of the total observed variation and the non-time correlated or purely "shock" variations. In this way, the total observed variation in permanganate and kappa number was presented as: Total variation = Time patterned variation + Shock variation.

Knowing this relationship, analysis of the total permanganate and kappa variation was accomplished by utilizing a time series to track the correlated portion of the total observed variation and computing the residual variation as the random shock component. Statistical tracking of these two variables by suitable techniques facilitated the calculation of a "statistical permission" to control. This "permission" was granted if an "out of control" condition occurred on either control chart.

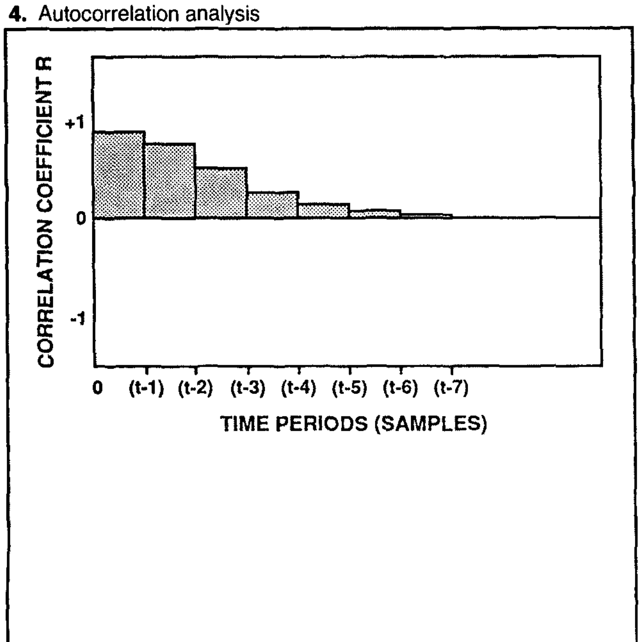
To allow the use of the time series techniques in conjunction with more recognized SPC methods such as XBAR and R charts, this time series was displayed in standard control chart format. Calculations of control limits were altered, however, because time series are not normally distributed, so standard SPC limits were not valid. In this case, it was found that more effective limits could be established by analyzing the particular mill's process data and the base value of the time patterned variation determined.

The random shock portion of the variation was by definition independent and was also found to be normally distributed. This allowed the use of standard Shewhart techniques with this portion of the analysis.

3. Capability plot



4. Autocorrelation analysis



Utilizing these techniques, identification of nonprobable events in the permanganate and kappa number data were categorized into two classes: common (time repetitive) causes of disturbance or special (random isolated) causes. By using these charts to calculate a permission to control, which was generated if one of these two types of causes was present, SPC was included in the closed-loop control strategy. Once control permission was ascertained, the corresponding temperature or alkali adjustments were computed using appropriate process relationships. This accomplished the first goal of the "best of both worlds" control scheme: minimizing deviation from process target via elimination of over- or under-control.

Tracking the causes of disturbances

The second major objective to be obtained from the integration of classical SPC was the ability to identify and track causes of process disturbances, allowing for long-term process improvement. This was accomplished in a real-time control system by identifying process variables that were suspected of having an effect on permanganate and kappa numbers and statistically tracking them in conjunction with the permanganate and kappa number variables. Data for each tracked variable was time-shifted so that any disturbances in permanganate and kappa numbers were time-traced to the appropriate point in history that could have contributed to the permanganate and kappa disturbance. This was dependent upon production rate, among other things.

By maintaining a history of correlated incidents, it was possible to assemble a Pareto analysis of causes of permanganate and kappa disturbances, and target areas for attention were highlighted. This facilitated the continuous improvement activities that were desirable for long-term improvement in competitive position.

Can this be done on-line and in real time?

Practical operation of such a control strategy for closed-loop control necessitated the following:

1. Automating charting and statistical analyses
2. Easy to use, concise operator interface
3. Automating tracking of assignable causes
4. Integration into the balance of the digester control system.

This would logically occur in an environment where all of these functions could be performed simultaneously and where all the pertinent data would be readily available.

The most common solution that has evolved in the continuous process industries for these types of situations is the use of a distributed control system. In a distributed control system, all of the capabilities exist for input and output of information to and from the process, as well as the computational capabilities required for the statistical operations. The fact that all of these functions are integrated on the same communications network allows the operator interface complete access to all information utilized in the control scheme. An additional advantage of this type of system is that the permanganate and kappa control logic is performed in the same distributed control system hardware where all of the standard regulatory and other advanced controls reside. This is desirable because of the interactive nature of many of the control functions present in a pulping operation. The implementation of this control scheme in a distributed control architecture also allows for all appropriate history storage and reporting considerations to be addressed within the same system, reducing data handling and communication problems.

These conditions were found to successfully facilitate the use of SPC in the fully closed-loop control of digester permanganate and kappa numbers.

Results

The previously described control strategy has been successfully implemented in operating mill systems. The permanganate and kappa control functionality was included as part of advanced control applications installed for continuous digester optimization.

Preliminary results vary for each of the mills involved, but in all cases there was an improvement over the previous control method or algorithm.

The magnitude of the improvement was often found to be dependent on the type of variation being experienced. In some cases, the bulk of the total variation in digester permanganate and kappa numbers was found to be predominantly time dependent, with regular repetitive disturbance patterns existing. Successful identification of the causes of these patterns has led to sustained improvement in at least one instance. In other cases, purely random shock-type disturbances predominated. In cases such as these, the magnitude of improvement in immediately measurable control was the largest improvement.

The methods employed in this control application, which utilizes moderately complex statistical techniques, were found to have good operator acceptance because the final presentation of the statistical information was in a standard "control chart" form, which was either already familiar to the operators or easily assimilated. The operator interface was constructed to summarize the results in a user-friendly manner and was well integrated with the other facets of the total control system.

Conclusions

We came to the following conclusions:

1. Statistical process control is a viable method for closed-loop control of digester permanganate and kappa numbers.
2. This method accomplishes the reduction of over- and under-control and provides information conducive to continuous process improvement.
3. All permanganate and kappa number data analyzed displayed significant autocorrelation, such that the use of conventional SPC methods could provide for misleading conclusions.
4. This type of control strategy integrates well into a distributed control system as part of an advanced control application.
5. The type and causes of permanganate and kappa number variation differ for each mill.☐

Literature cited

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