Controversies and Contradictions in Statistical Process Control

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Statistical process control (SPC) methods are widely used to monitor and improve manufacturing processes and service operations. Disputes over the theory and application of these methods are frequent and often very intense. Some of the controversies and issues discussed are the relationship between hypothesis testing and control charting, the role of theory and the modeling of control chart performance, the relative merits of competing methods, the relevance of research on SPC and even the relevance of SPC itself. One purpose of the paper is to offer a resolution of some of these disagreements in order to improve the communication between practitioners and researchers.

Introduction

STATISTICAL methods play a vital role in the quality improvement process in manufacturing and service industries. As evidence of the interest in statistics among quality professionals, the membership of the Statistics Division of the American Society for Quality (ASQ) (11,000) is roughly 60% of that of the entire American Statistical Association (18,000).

As pointed out by Woodall and Montgomery (1999), there are a number of disputes in the area of statistical quality control (SQC). There are differences of opinion in all areas of statistical science, but disagreements tend to be more common and more intense in the quality area. This could be due in part to the diversity of those working in the quality field, including quality gurus and their followers, consultants, quality engineers, industrial engineers, professional practitioners, statisticians, managers, and others. Another contributing factor to disagreements is competition for the large investments companies make in quality improvement and quality certification programs.

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Statistical process control (SPC), a sub-area of SQC, consists of methods for understanding, monitoring, and improving process performance over time. The purposes of this paper are to give an overview of some of the controversial issues in SPC, to outline some of the contradictory positions held by past and present leaders in this area, and, in some cases, to offer a middle ground for the resolution of conflicts. It is hoped that practitioners will better understand how SPC research can improve the use of methods in practice. Also, it is hoped that SPC researchers will better understand how their models fit into the context of an overall SPC strategy.

Some basic concepts of SPC are discussed in the next section. The debate over the relationship between hypothesis testing and control charting is reviewed in the third section. In the fourth section, the role of theory is covered and the usefulness of determining the statistical performance of control charts is supported. Various alternatives to Shewhart control charts are then discussed. The sixth section contains conflicting views on the role of SPC and research in SPC. Conclusions are given in the final section.

Some Concepts of SPC

Understanding of the variation in values of a quality characteristic is of primary importance in

SPC. 'Common cause' variation is considered to be due to the inherent nature of the process and cannot be altered without changing the process itself. 'Assignable (or special) causes' of variation are unusual shocks or other disruptions to the process, the causes of which can and should be removed. One purpose of control charting, the featured tool of SPC, is to distinguish between these two types of variation in order to prevent overreaction and underreaction to the process. The distinction between common causes and assignable causes is context dependent. A common cause today can be an assignable cause tomorrow. The designation could also change with a change in the sampling scheme. One wants to react, however, only when a cause has sufficient impact that it is practical and economic to remove it in order to improve quality.

Control charts are used to check for process stability. In this context, a process is said to be "in statistical control" if the probability distribution representing the quality characteristic is constant over time. If there is some change over time in this distribution, the process is said to be "out of control." This traditional definition of "statistical control" has been generalized over the years to include cases for which an underlying statistical model of the quality characteristic is stable over time. These useful generalizations include, for example, regression, variance component, and time series models.

For continuous quality characteristics, specification limits are often given in practice. An item is considered to be "O.K." if the value of its quality characteristic is within the specification limits and "not O.K." otherwise. Deming (1986) and many others have argued that meeting specification limits is not sufficient to ensure good quality and that the variability of the quality characteristics should be reduced such that, as Deming (1986, p. 49) describes it, "specifications are lost beyond the horizon." Thus, for many quality characteristics, quality improvement corresponds to centering the probability distribution of the quality characteristic at a target value and reducing variability. Taguchi (1981, p. 14) advocated reduction of variability until it becomes economically disadvantageous to reduce it further.

To use a control chart such as the $\overline{X}$-chart to monitor the process mean or the R-chart to monitor variability, samples are taken over time and values of a statistic are plotted. For the type chart introduced by Shewhart (1931, 1939), an out-of-control signal

is given by the chart as soon as the statistic calculated from a sample falls outside control limits. These limits are usually set at ± 3 standard errors of the plotted statistic from a centerline at its historical average value. The formula for the calculation of the standard error is usually based on a distributional assumption, e.g., the binomial model for a p-chart used to monitor proportions. The resulting control limits are referred to as "three-sigma" limits. Other rules are also used for signaling an out-of-control situation based on "non-random" patterns on the chart. Many of these patterns are given in the Western Electric Handbook (1956).

It is very important to distinguish between use of a control chart on a set of historical data to determine whether or not a process has been in statistical control (Phase 1) and its use prospectively with samples taken sequentially over time to detect changes from an in-control process (Phase 2). The use of control charts in Phase 1 is usually iterative. Much work, process understanding, and process improvement is often required in the transition from Phase 1 to Phase 2.

It is assumed here that the reader is somewhat familiar with the construction and use of control charts. For detailed introductions to these ideas, the reader is referred to Wheeler and Chambers (1992), Montgomery (1996), Ryan (2000), or Woodall and Adams (1998).

Control Charting and Hypothesis Testing

For the basic Shewhart-type control chart with no supplementary signal rules, the process is considered to be in-control if the plotted statistic falls within the control limits and out-of-control otherwise. Thus, there is a yes/no decision based on the value of a statistic and decision regions. This is a structure similar, at least on the surface, to that used in testing hypotheses. Thus, the reader may be surprised over the strong disagreements regarding the relationship between control charting and repeated hypothesis testing.

Some authors write that control charting and hypothesis testing are equivalent or very closely related. Juran (1997, p. 79), for example, referred to the control chart as "a perpetual test of significance." Box and Kramer (1992) stated that "process monitoring resembles a system of continuous statistical hypothesis testing." Vining (1998, p. 217) wrote

The current peer review literature, which represents the standard for evaluating the effectiveness and efficiency of these methodologies, tends to view the control chart as a sequence of hypothesis tests.

Vining then justifies his hypothesis testing view stating that it better reflects statistical thinking in showing ties between two important areas of statistics, provides a formal basis for evaluating properties of control charts, and justifies use of the cumulative sum (CUSUM) control chart.

On the other side of the issue, Deming (1986, p. 369) stated (without elaboration)

Some books teach that use of a control chart is test of hypothesis: the process is in control, or it is not. Such errors may derail self-study.

Also, Deming (1986, p. 335) wrote

Rules for detection of special causes and for action on them are not tests of a hypothesis that a system is in a stable state.

Nelson (1999) takes a similar view. Wheeler (1995, p. 17 and Chapter 19) and Hoerl and Palm (1992) also emphasize the differences between control charting and hypothesis testing.

Deming (1986, p. 272) strongly advocated the use of control charts, but argued emphatically against the use of hypothesis testing.

Incidentally, the chi-square and tests of significance, taught in some statistical courses, have no application here or anywhere.

Deming argued that practical applications in industry required "analytical" studies because of the dynamic nature of the processes for which there is no well-defined finite population or sampling frame. He held that hypothesis testing was inappropriate in these cases. Hahn (1995) provides a clear summary of the distinction between what Deming referred to as analytical and enumerative studies.

As pointed out by Woodall and Faltin (1996), Shewhart (1939, p. 40) seemed to take more of a middle ground in this debate since he wrote

As a background for the development of the operation of statistical control, the formal mathematical theory of testing a statistical hypothesis is of outstanding importance, but it would seem that we must continually keep in mind the fundamental difference between the formal theory of testing a statistical hypothesis and the empirical theory of testing of hypotheses employed in the operation of statistical control. In the latter, one must also test the hypothesis that the sample of data was obtained under conditions that may be considered random.

Woodall and Faltin (1996) also point out that control charting and hypothesis testing are similar, for example, in the respect that unnecessarily large sample sizes may result in reactions to small effects of no practical significance.

Some of the disagreement over the relationship between control charting and hypothesis testing appears to result from a failure to distinguish between Phase 1 and Phase 2 applications. The theoretical approach to control charting in Phase 2, in which the form of the distribution is assumed to be known along with values of the in-control parameters, does closely resemble repeated hypothesis testing, especially if one considers an assignable cause to result in a sustained shift in the parameter of interest. In some cases there is mathematical equivalence. In practical applications of control charts in Phase 1, however, no such assumptions are or can be made initially and the control chart more closely resembles a tool of exploratory data analysis. As Hoerl and Palm (1992) explain, the underlying model then is only that one has a series of independent random observations from a single statistical distribution. The control chart rules are used to detect deviations from the model, including the model assumptions themselves.

At best the view that control charting is equivalent to hypothesis testing is an oversimplification. At worst the view can prevent the application of control charts in the initial part of Phase 1 because of the failure of independence and distributional assumptions to hold.

Role of Theory

To measure the statistical performance of a control chart in Phase 1 applications, one considers the probability of any out-of-control signal with the chart. The false-alarm rate, for example, is the probability of at least one signal from the chart given that the process is in statistical control with some assumed probability distribution. This approach is related to the "analysis of means" discussed by Wheeler (1995, Chapter 18) and Ryan (2000). In Phase 2, the probability of a signal on any one sample is sometimes used if the successive statistics plotted are independent, as may be the case with a basic Shewhart-type chart. More commonly, some parameter of the run length distribution is used. The run length is the number of samples required for a signal to occur. The average run length (ARL) is the most frequently used parameter, although the run length distribution is often skewed to the right.

The calculation of any statistical measure of performance requires an assumption about the form of the probability distribution of the quality characteristic. Certainly most of the theoretical and simulation studies of the performance of control charts for variables data have been based on the assumptions of an underlying normal distribution and independence of samples over time. Also, the control chart constants used in practice to calculate the control limits of the $\overline{X}$ and R charts are based on an assumption of normality, although Burr (1967) showed that non-normality appears to have little effect on their values. To first use a control chart in practice, however, no assumptions of normality or independence over time need to be made. In fact, distributional assumptions cannot even be checked before a control chart is initially applied in a Phase 1 situation because one may not have process stability. As one works within Phase 1 to remove assignable causes and to achieve process stability, the form of the hypothesized underlying probability distribution becomes more important in determining appropriate control limits and in assessing process capability. To interpret a chart in Phase 1, practitioners need to be aware that the probability of signals can vary considerably depending on the shape of the underlying distribution for a stable process, the degree of autocorrelation in the data, and the number of samples.

Wheeler (1995) states, "the assumptions used for the mathematical treatment become prohibitions which are mistakenly imposed upon practice." Hoerl and Palm (1992) take a similar position that may also be somewhat overstated. Many authors, however, do imply that the normality and independence assumptions are required in practice without necessarily stating this explicitly. Often this is because they want to give the probability of a false alarm with a Phase 2 $\overline{X}$-chart to be .0027 for each sample, but this value itself is not accurate unless the in-control parameters are estimated with large samples, as shown by Quesenberry (1993).

Distributional and independence assumptions in theoretical studies of Phase 2 should not be construed as requirements in practical applications of the initial stages of Phase 1. The mathematical approach is very useful, however, in showing how control charting methods will tend to behave under various scenarios. Many papers have been written on the statistical performance of control charts, primarily for Phase 2. According to Pearson (1967), the more mathematical treatment began in England after a

visit there by Shewhart in 1932. It is doubtlessly disturbing to many practitioners that researchers tend to neglect Phase 1 applications and the vitally important practical considerations of quality characteristic selection, measurement and sampling issues, and rational subgrouping. With the exception of measurement error analysis, however, most of the latter issues cannot be easily placed into a general mathematical framework. Because of this fact, these important practical issues are rarely mentioned in the SPC research literature.

It is important to understand the robustness of control chart performance to the standard theoretical assumptions. There is considerable disagreement regarding robustness. Wheeler (1995, p. 288) states, for example, that the effect of autocorrelation on the control limits of the control chart for individuals data will not be significant until the lag-one autocorrelation coefficient is .7 or higher. Maragah and Woodall (1992), however, show that much lower levels of autocorrelation can have a substantial effect on the chart's statistical performance. Padgett, Thombs, and Padgett (1992), among others, show the effect of non-normality and autocorrelation on control charts such as the Shewhart $\overline{X}$-chart. There appears to be a wide difference of opinion on how much robustness is needed in practical applications, so there may always be some disagreement on this issue.

The effect and implications of autocorrelation have been topics of frequent discussion and debate in the SPC literature. See, for example, Montgomery and Mastrangelo (1991), Box and Kramer (1992), Hoerl and Palm (1992), and Woodall and Faltin (1993). Autocorrelation often reflects increased variability. Thus, the first two options to consider should be to remove the source of the autocorrelation or to use some type of process adjustment scheme such as those discussed by Box and Luceño (1997) and Hunter (1998). Control charting can be used in conjunction with process adjustment schemes, and Box and Luceño (1997) emphasized that the two types of tools should be used together. Only if these first two options prove infeasible should one consider using stand-alone control charts for process monitoring such as those discussed by Lu and Reynolds (1999), Lin and Adams (1996), and Adams and Lin (1999). One should be aware that in Phase 2, the statistical performance of standard control charts with the usual limits can be greatly affected by autocorrelation. This is rightly so since the charts are designed to detect departures from an independent, identically

distributed process with in-control parameter values. Upon reaching the latter stages of Phase 1 and in Phase 2, it pays to study distributional characteristics and the degree of autocorrelation to prevent using a chart that produces many non-informative out-of-control signals.

To some, however, the statistical performance of control charts is of little or no importance. Deming (1986, pp. 334–335), for example, stated

> The calculations that show where to place the control limits have their basis in the theory of probability. It would nevertheless be wrong to attach any particular figure to the probability that a statistical signal for detection of a special cause could be wrong, or that the chart could fail to send a signal when a special cause exists. The reason is that no process, except in artificial demonstrations by use of random numbers, is steady, unwavering. It is true that some books on the statistical control of quality and many training manuals for teaching control charts show a graph of the normal curve and proportions of area thereunder. Such tables and charts are misleading and derail effective study and use of control charts.

Wheeler (1995, p. 15) and Neave (1990, p. 78) go even further to argue that consideration of the theoretical properties of control charts, the "probabilistic" approach, actually reduces the usefulness of the techniques. As discussed by Woodall and Montgomery (1999), Deming's view seemed to be that models are not useful in control charting since none have unchallengable assumptions. Given his stature in the quality area, Deming's views have had considerable impact.

Deming's position that no process is steady and unwavering contradicts the premise of his principle, however, that stable processes should not be adjusted.

> If anyone adjusts a stable process to try to compensate for a result that is undesirable, or for a result that is extra good, the output that follows will be worse than if he had left the process alone.

Deming, 1986, p. 327.

Deming illustrates this principle with one of his well-known funnel experiments where marbles are dropped toward a target marked on a table. Variation about the target is increased if the funnel is moved in an attempt to correct for random errors. Although it is a mistake to adjust an on-target, in-control process, it can be of benefit to adjust autocorrelated processes, as illustrated by MacGregor (1990). In these cases Deming's funnel experiment has often been misinterpreted and become a barrier

in practice to consideration of adjustment methods such as those discussed by Box and Luceño (1997).

Deming's objection to measures of statistical performance of control charts because no process is stable can be overcome at least in part by modeling the instability of the process distribution. For example, one might consider a normal distribution with constant variance, but with a mean that itself is normally distributed. This approach is useful in situations for which there is more than one component of common cause variability. See, for example, Woodall and Thomas (1995) and Laubscher (1996).

It is odd that Deming, as quoted by Neave (1990, p. 249), rejected the mathematical theory of control charting since he stated bluntly,

> Experience teaches nothing unless studied with the aid of theory.

It is often argued that Shewhart charts with 3-sigma limits should be used because experience shows this to be the most effective scheme and because Shewhart (1931, p. 277) stated that this multiple of sigma "seems to be an acceptable economic value." Given this reliance on Shewhart's opinion, however, it is somewhat disconcerting to read Juran's (1997) surprising account that "Shewhart has little understanding of factory operations" and could not communicate effectively with operators and managers. Juran's view of Shewhart, however, differs considerably from Shewhart's other contemporaries as evidenced in "Tributes to Walter A. Shewhart" published in *Industrial Quality Control* in August, 1967.

Other Control Charts and Methods

CUSUM and EWMA Charts

Deming's view was that the three-sigma Shewhart chart was unsurpassed as a method for detection of assignable causes.

> The Shewhart control charts do a good job under a wide range of conditions. No one has yet wrought improvement.

Deming (1993, p. 180).

> Shewhart contrived and published the rule in 1924—65 years ago. Nobody has done a better job since.

Deming, as quoted by Neave (1990, p. 118).

Why should control charting be exempt from Deming's exhortation to constantly and forever improve? In order to even consider the possibility that the Shewhart type chart could be enhanced or another control charting method could be better than the

Shewhart chart under any situations, operational definitions of "good" and "better" are required. As Deming (1986, p. 276) wrote

> Adjectives like good, reliable, uniform, round, tired, safe, unsafe, unemployed have no communicable meaning unless they are expressed in operational terms of sampling, test, and criterion.

With operational definitions it seems that in comparisons of control chart performance one is led inexorably to comparisons of statistical performance under assumed models. As Deming argued, experience is not sufficient as a guide within itself. It has been shown using statistical performance, for example, that cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) charts are much more effective than Shewhart charts in detecting small and moderate-sized sustained shifts in the parameters of the probability distribution of a quality characteristic. See, for example, Montgomery (1996, Chapter 7). The use of runs rules with the Shewhart chart, however, narrows the gap in performance somewhat, as shown by Champ and Woodall (1987). In some cases EWMA and CUSUM charts are very useful, but they are not meant to completely replace the Shewhart chart which can be used to detect a wider assortment of effects due to assignable causes. It is frequently recommended that Shewhart limits be used in conjunction with a CUSUM or EWMA chart.

Pre-control

One highly controversial method offered as an alternative to control charting is "pre-control." With pre-control there are no control limits based on process performance and no attention paid to whether or not the process is in statistical control. The method is based on the specification limits, the range of which is divided into four parts of equal length. The middle two parts comprise the "green zone." The outer two parts within the specification limits comprise the "yellow zones" and the region outside the specification limits corresponds to the "red zone." Various sampling and decision rules are set up such that the process is allowed to operate as long as measurements don't fall into the red zone or into the yellow zone too often. See Bhote (1988, 1991), Ledolter and Swersey (1997a), and Steiner (1997–98) for more details on pre-control.

As Ledolter and Swersey (1997a) point out, advocates of pre-control typically promote the idea with a great deal of hyperbole. Bhote (1988), for example, uses the chapter title "Control Charts vs. Pre-control: Horse and Buggy vs. the Jet Age." It is difficult to make meaningful comparisons between pre-control and control charts since there are typically no clear statistical objectives or assumptions made for pre-control. Upon careful study, Ledolter and Swersey (1997a) identify specific situations for which pre-control has value, but conclude in general that the method is not an adequate substitute for statistical control charts. If one follows the view of Deming and others that models should not be used to determine statistical properties, then it becomes impossible to argue effectively against pre-control or any other such method. Even though Wheeler (1995) argues strongly against the probabilistic approach, for example, he uses alarm probabilities and ARLs to argue against the use of two-sigma limits with Shewhart control charts and against pre-control. As Wheeler (1995, pp. 205–206) explains, he reluctantly and cautiously uses the probabilistic approach because of the benefit of its generality. He holds, however, that only gross differences in theoretical performance are likely to transfer over into practical applications.

Advocates of pre-control present a misleading impression of control charting practice. For example Bhote (1988, p. 35) states that control charts which show that a process is in statistical control also indicate that process performance is good. This ignores the fact that capability analyses are performed after it is determined that a process is in statistical control. Since pre-control cannot be used to determine statistical control, the common use of process capability indices in the application and discussion of pre-control is meaningless. Unfortunately, a lot of energy in the SPC area goes toward debating with those, such as many of the advocates of pre-control, who do not understand control charting concepts and offer inferior methods.

Impact of New Methods

Another unfortunate fact is that some useful advances in control charting methods have not had a sufficient impact in practice. As Crowder et al. (1997) state

> There are few areas of statistical application with a wider gap between methodological development and application than is seen in SPC.

The body of SPC knowledge required, for example, for the certified quality engineer (CQE) exam of ASQ consists almost entirely of material covered in the Western Electric Handbook (1956). Disturbingly,

ASQ lists Bhote (1991) as one of eight books suggested in the reference materials for the statistical principles and applications portion of the CQE exam. This is very odd, to say the least, since Bhote (1991) refers to control charting as "a total waste of time" and states that classical design of experiments as described by Box, Hunter, and Hunter (1978) is of "low statistical validity" and dominated in all practical aspects by the methods of Dorian Shainan. Both control charting and classical design of experiments form substantial parts of the required CQE material. In the design area, Bhote (1991) advocates the variable search method of experimentation shown by Nelson (1989), Amster and Tsui (1993) and Ledolter and Swersey (1997b) to be inefficient. Moore (1993) provides a more detailed review of Bhote's 1991 book.

It is clear that the infusion of new ideas into the accepted body of SPC knowledge has been very slow. Udler and Zaks (1997) cite the "weight of quality assurance bureaucracies" and "the comfort of existing systems in professional quality circles" for this situation. Another frequently mentioned factor is that many practitioners do not have strong enough backgrounds in statistics to move beyond the simpler basic methods. Also, so many ideas, methods, and variants of methods have been proposed over the years, many of little practical value, that it becomes difficult to separate useful methods from the rest. Regardless of the reasons for their lack of wide acceptance, there have been many techniques developed that could greatly increase the usefulness of SPC in some common situations. These include process adjustment strategies, regression-based methods, multivariate methods, use of variance components, variable sampling methods, and change-point techniques, to name a few. See the panel discussion edited by Montgomery and Woodall (1997) for an overview of many of these methods and relevant references. The relative merits of competing methods are sometimes hotly debated. See, for example, Woodall (1986) for a critique of the economic design of control charts and Quesenberry (1998, 1999) for a debate on short-run SPC.

Two Ineffective Methods

On the other hand, there are some very commonly used methods which are ineffective and whose use should be discontinued. For example, a very widely used supplementary rule for a Shewhart chart is for a signal to be given if there are a number of consecutive points plotted which are either all steadily increasing or all steadily decreasing. Deming (1986, pp. 320–

321, p. 363) advocates this rule with seven or more consecutive points and it is recommended by AIAG (1991). It has been shown by Davis and Woodall (1988); Walker, Philpot, and Clement (1991); and others, however, that this rule is ineffective in detecting a trend in the underlying mean of the process, the situation for which it was intended. Even though the rule seems intuitively reasonable, its primary effect is to inflate the false-alarm rate.

Also, with individual observations collected over time, it is standard practice to use a moving range chart to detect changes in variability. Rigdon, Cruthis, and Champ (1994) and Sullivan and Woodall (1996), among others, have shown that the moving range chart is ineffective for this purpose. If one wishes to detect sustained changes in variability in Phase 1, the change-point method described by Sullivan and Woodall (1996) is much more effective. The moving range chart, however, remains part of the ASQ CQE exam material and the ineffective trend rule is included in the references recommended by ASQ for this exam.

Relevance of SPC and SPC Research

The manufacturing environment in which SPC is used is changing rapidly. There are, for example, trends toward shorter production runs, much more data, higher quality requirements and greater computing capability. Gunter (1998) argues that control charts have lost their relevance in this environment, stating

> The reality of modern production and service processes has simply transcended the relevance and utility of this honored but ancient tool.

Banks (1993) and Hoyer and Ellis (1996 a–c), among others, have been very critical of research on SPC. Banks writes, for example,

> It is probably past time for university researchers to drop stale pseudo-applied activities (such as control charts and oddly balanced designs) that only win us a reputation for the recondite.

In my view the role of SPC in understanding, modeling, and reducing variability over time remains very important. There needs to be a quicker transition, however, from the classical methods to some of the newer approaches when appropriate. There are useful areas of research as discussed by Woodall and Montgomery (1999) and Stoumbos et al. (2000). The scope of SPC needs to be broadened to include an understanding of the transmission of variation through-

out the manufacturing process. This will require more sophisticated modeling and the incorporation of more engineering knowledge of the processes under study.

Conclusions

Various differences in opinion have been given in this paper on issues regarding control charts. In the author's view many of the disagreements are essentially communication problems which can be resolved. One communication problem is that researchers rarely, if ever, put their sometimes narrow contributions into the context of an overall SPC strategy. There is a role for theory in the application of control charts, but theory is not the primary ingredient for most successful applications. Control charting is related closely to hypothesis testing only under the mathematical framework used to determine the statistical performance of the charts. The associated assumptions are not required for control charts to be used initially in practice. The form of any underlying distribution and the degree of autocorrelation, however, become increasingly important components in the interpretation of control charts as one progresses in Phase 1 and in the assessment of their expected performance in Phase 2. Study of the statistical performance of charts is very important because it provides insight into how charts work in practice and it provides the only way to effectively compare competing methods in a fair and objective manner.

The methods developed in the first half of this century by Shewhart and others are still very useful in many current applications. Their familiarity and simplicity relative to other methods can often compensate for loss in efficiency. In our changing manufacturing environment, however, it is important to consider some of the methods developed more recently such as those for several related quality characteristics, multiple processes, and more sophisticated sampling plans. Infusion of new ideas into the body of commonly accepted SPC knowledge has been much too slow and has led to much of the criticism regarding the relevance of SPC in the current manufacturing environment.

Acknowledgments

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