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Research Issues and Ideas in Statistical Process Control

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ABSTRACT

An overview is given of current research on control charting methods for process monitoring and improvement. The discussion includes a historical perspective along with ideas for future research. Research topics include, for example, variable sample size and sampling interval methods, economic designs, attribute data methods, charts based on autocorrelated observations, multivariate methods, and nonparametric methods. Recommendations and references are provided to those interested in pursuing research ideas in statistical process control (SPC). Some issues regarding the relevance of SPC research are also discussed.

Key Words: Control Charting, Statistical Process Control, Statistical Quality Control.

BACKGROUND

STATISTICAL quality control (SQC) and improvement is a branch of industrial statistics which includes, primarily, the areas of acceptance sampling, statistical process monitoring and control (SPC), design of experiments, and capability analysis. Briefly summarizing these, acceptance sampling methods are used in industry to make decisions regarding the disposition of "lots" of manufactured items, including accepting or rejecting individual lots. SPC techniques are employed to monitor production processes over time to detect changes in process performance. Designed experiments are run to identify important factors affecting process and product quality, referred to as screening or characterization, and to identify the specific levels of the important factors that lead to optimum (or near-optimum) performance. For example, levels of factors can be determined that result in higher yields, improved quality, and lower costs. The objective of capability analysis is to assess whether or not a process is capable of meeting specification limits on key quality characteristics. These specification limits are usually imposed by customers. Another important aspect of capability analysis is to determine the performance of a measurement system. This is often referred to as gauge or measurement systems capability analysis.

Until the 1980's, SQC textbooks gave roughly equal emphasis to acceptance sampling and SPC. Since then, acceptance sampling has been greatly deemphasized. Certainly one of the primary reasons for this was the influence of W. E. Deming who argued strongly and eloquently against the widespread use of acceptance sampling, calling it "too late, costly, and ineffective." This does not imply that the techniques are without potential applications; for an insightful view on the role of acceptance sampling, the reader is referred to Vardeman (1986). As a general observation, however, researchers new to SQC should be aware of the fact that it is relatively difficult now to publish papers on acceptance sampling topics unless a strong link to an important practical problem can be established.

Designed experiments have received increasing attention over the last two decades. Some recent SQC textbooks omit acceptance sampling entirely, giving roughly equal weight to SPC and design of experiments. Much of the recent interest in quality improvement using designed experiments has been due to the work on robust parameter design by Genichi Taguchi. His methods were introduced to the United States in the early 1980's. Taguchi presented a methodology for using designed experiments to make products and processes less sensitive to variation transmitted by factors that are difficult to control precisely. Taguchi's ideas were initially introduced and advocated by entrepreneurs, and the methodology did not receive extensive peer review for several years. The result of the peer-review process revealed that while Taguchi's philosophy and objectives were sound, some of his technical and statistical methods were seriously flawed. For a discussion of these ideas, see Box, Bisgaard, and Fung (1988); Nair (1992); Myers and Montgomery (1995); and Montgomery (1992, 1997). Another reason for the overall trend away from acceptance sampling and toward designed experiments is due to the recognition that statistical methods become much more effective the further upstream they are applied in each part of the production process, including product design and development, manufacturing, and distribution.

For a review of recent developments in process capability analysis, the reader is referred to Rodriguez (1992). There is a considerable amount of ongoing research on the use of capability indices. These one-number summaries of production process capability are widely used (and misused) in industry. There is much less research reported on measurements systems capability analysis to determine the performance of a gauge or measurement system. The performance characteristics investigated include accuracy or bias in the measurements, linearity (including calibration), and precision. Most SQC research has focused on precision. For more information, see Burdick and Larsen (1997); Borror, Montgomery, and Runger (1997); Montgomery and Runger (1993a, 1993b); and Vardeman and Van Valkenburg (1999).

INTRODUCTION

One purpose of this paper is to encourage research in the area of control charting and SPC. As a general definition, we include in this area any statistical method designed to detect changes in a process over time. Often this problem is modeled mathematically as detecting changes over time in the parameter or parameters of an underlying probability distribution.

One should be aware that there are some individuals in the SPC area who have opposed any mathematical modeling of control charts. W. E. Deming is included in this group; for example, see Deming (1986, p. 369) and Neave (1990, pp. 78-82). Their argument is that Shewart's ideas were based on empirical results, not mathematical models and derivations. Their position seems to be that no models are useful in this application because none can be postulated that have unchallengeable assumptions. This argument seems to be unique to SPC within the statistical sciences. For more discussion on this point, see Montgomery (1998). It appears from Pearson (1935, 1967) that mathematical modeling and analysis concerning control chart performance began in Great Britain after a visit there by Shewhart in 1932.

There are a number of other disputes regarding SPC methods, including the relationship between hypothesis testing and control charting, the robustness of chart performance to violations of assumptions, the relative merits of competing methods, and the relevance of research. Some of these issues are discussed by Woodall and Faltin (1996) and Woodall (1999). There are differences of opinion, of course, in all areas of statistical science, but disputes seem to occur more often and with greater intensity in SQC. This can at times be very frustrating, but it does make working in the quality area interesting. The diversity of strong, often conflicting, opinions reflects the diversity of those in the quality area, including quality gurus and their followers, consultants, quality engineers, industrial engineers, professional practitioners, and statisticians, among others. A contributing factor to disputes is the intense competition for the large amount of monies companies invest in quality improvement and certification programs.

The basic fundamentals of SPC and control charting were proposed by Walter Shewhart in the 1920's and 1930's. Until the mid to late 1970's there were many important advances but relatively few individuals conducting research in the area compared to other areas of applied statistics. Research activity has greatly increased since about 1980 onward. Much of the increase in interest was due to the quality revolution, which was caused by an increasingly competitive international marketplace. Improvements in quality were required for survival in many industries. The need for continuous improvement and higher quality is likely to remain as a permanent feature of the business environment. Another cause of the increase in research activity may be due to the greatly increased pressure for faculty research and publication in colleges and universities. This latter factor, of course, would apply to all areas of statistics, not just SPC.

Many of the methods initially proposed for statistical monitoring and control were ad hoc in nature. These methods were used simply because they seemed to work and were reasonable. Also, the methods were designed for simplicity and ease of calculation; otherwise they could not be used in practice. For example, the use of the sample range, instead of the sample variance, to estimate variability is still a common practice in applications of SQC. Furthermore, SPC methods were developed and applied largely in the discrete parts industries. This application environment was typically one in which process data was relatively difficult to collect; parts were sampled and measured manually at relatively long time intervals, and only a few parts were evaluated each day for purposes of process monitoring and control. Much of the research in the 1980's involved studying the statistical performance of methods which were already widely used in industry.

Today's SPC application environment is often considerably different. On-line measurement, data capture, and analysis through hierarchical, distributed computing systems are becoming the norm in many industrial settings, from discrete parts to the chemical and process industries. This has totally changed the nature of the data available for process monitoring and control. In some instances, process data is available every second or every few minutes on hundreds of process variables and product characteristics.

The literature on SPC is quite large now and growing rapidly. Thus, compiling a complete literature survey would be very difficult, requiring several volumes. The bibliography by Woodall (1997) of SPC methods based on attribute data contained roughly 250 journal articles. The literature on methods based on continuous variables could be fifteen to twenty times this size. It is also becoming increasingly difficult to keep track of current SPC research since there are a large number of papers appearing in many different technical journals.

Many types of statistical methods have been successfully incorporated into SPC procedures. Examples include regression methods, multivariate analysis, time series, and nonparametric methods. Thus no matter what one's primary area of interest in statistics, chances are there is some useful application or potential application of it in SPC.

CONTROL CHARTING IDEAS

To apply a control chart, one must observe data from a process over time. Decisions are required about the variables to measure, the sample size, the time between samples, and the decision rules.

Variation remaining in a stable process reflects "common causes" which cannot be removed easily from the process without fundamental changes in the process itself. If the underlying probability distribution of the quality characteristic is stable over time, the process is said to be in "statistical control." One purpose of a control chart is to detect unusual variation due to "assignable causes." When the control chart signals the possible presence of an assignable cause, an effort is made to find and remove it from the process if this action would reduce variability or improve quality. It is also important to detect improvements in process performance.

The basic Shewhart X-chart for monitoring the mean of a process consists of a center line at the historical process level and upper and lower control limits. Sample means are plotted over time. An "out-of-control" signal is given when a sample mean falls beyond the control limits. The control limits are most often set at +/-3 sigma from the centerline, where "sigma" is the estimated standard error of the sample means. Other methods have been proposed to improve sensitivity to small and moderate-sized shifts in the mean. In particular, runs rules have been used to signal for other unusual patterns on the chart, such as having eight sample means in a row either all above or all below the centerline. Runs rules improve the sensitivity, but also increase the number of false alarms. Complements to the Shewhart control chart include the cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) control charts. These latter methods allow information to be accumulated over time, which is not the case with the basic

Shewhart chart. For information on CUSUM charts, the reader is referred to Hawkins and Olwell (1998). See Lucas and Saccucci (1990) for a discussion of the EWMA chart. These charts are also discussed and illustrated in many basic SQC textbooks.

There are control charts for monitoring the variance of a process (R-chart and s-chart), the proportion of "non-conforming" items (p-chart and np-chart), and the average number of "non-conformities" on items (c-chart and u-chart). There are control charts proposed for monitoring the parameter (or parameters) of all the standard probability distributions, both discrete and continuous.

It is very important to distinguish between the retrospective analysis phase (Phase I) and the process monitoring phase (Phase II) in control charting. In Phase I, a set of data has been collected from a process. For an X-chart it is typically recommended that one have at least 20-25 samples of size 4-5 each. In Phase I, one checks for statistical control and estimates parameters to be used to determine the control limits for Phase II. This can be a challenging problem because shifts in the underlying distribution distort parameter estimation, which, in turn, masks the shifts. To study the statistical performance of a method used in Phase I, one should consider the probability of concluding that the process is not in statistical control when, in fact, it is and the power of detecting various departures from statistical control. In Phase II, statistical performance is usually measured by the probability of a signal, when one is considering only a basic Shewhart chart, or some parameter of the run length distribution. The run length is the number of samples required until an out-of-control signal is given. Often the average run length (ARL) is used, although run length distributions are often usually highly skewed to the right.

Most of the research on control charting is on Phase II performance. The Phase I problem is closely related to the analysis of means, although this relationship is usually overlooked. See Ryan (2000) for a discussion of analysis of means. Unfortunately, authors sometimes do not clearly specify whether their work applies to Phase I or Phase II. Some authors have proposed methods which purport to bypass the need for Phase I data (see, e.g., Hawkins (1995)).

SOME RESEARCH AREAS IN SPC

A few of the most active research areas in SPC are briefly summarized in this section. Some references are given which may be helpful to those interested in learning more about these areas.

MULTIVARIATE METHODS

Quality is generally determined by several quality characteristics which may be correlated. Multivariate charts take this correlation into account in monitoring the mean vector or variance-covariance matrix. There are multivariate generalizations of the CUSUM and EWMA charts. Once an out-of-control signal is given by a multivariate chart, it may be difficult to determine which variable (or variables) contributed to the signal. Various approaches to this problem have been proposed. For a review of multivariate SPC, the reader is referred to Wierda (1994), Lowry and Montgomery (1995), and Mason et al. (1997). Research activity in multivariate SPC now seems to be at its highest level, reflecting increased measurement and computing capability.

The performance of multivariate control charts in detecting process disturbances tends to deteriorate as the number of monitored variables increases (see Lowry and Montgomery (1995)). Furthermore, in the process industries where these techniques are likely to have a high payoff, one is likely to encounter large data sets with hundreds of variables, autocor-relation, missing data, non-alignment of sampling points, and many other problems that would render the application of conventional multivariate control charts very difficult. Consequently, there has been great interest recently in techniques for process monitoring that may be less affected by these problems. Under the assumption that a process that is described by a large number of variables actually moves in a much smaller subspace of these variables, techniques such as principal components, partial least squares, and regression adjustment methods have been proposed. For more information, see Hawkins (1991); MacGregor (1997); Kourti and MacGregor (1996); and Mastrangelo, Runger, and Montgomery (1996).

EFFECT OF ESTIMATION ERROR

In most evaluations and comparisons of control chart performance in Phase II, it is assumed that the in-control values of the parameters are known. In practice, however, the parameters must be estimated in Phase I. The effect of this estimation on control chart performance has been studied, but only for relatively few types of charts (see, e.g., Ghosh, Reynolds, and Hui (1981); Quesenberry (1993); and Chen (1997)). Much more research is needed in this area recognizing that the Phase II control limits are, in fact, random variables. Research shows that more data than has been traditionally recommended is needed to accurately determine control chart limits.

SHORT-RUN METHODS

In short production runs, there may not be enough data to accurately estimate process parameters. In fact, very little data may be available. Various methods have been proposed to deal with this situation. A thorough review of this area is given by Del Castillo et al. (1996); Hawkins (1995); and Woodall, Crowder, and Wade (1995).

AUTOCORRELATED DATA

The traditional model of an in-control process included stability of the distribution of the quality characteristic and independence of the observations over time. Various methods have been proposed for dealing with the often more realistic situation in which data are autocorrelated. In this situation, the emphasis shifts from checking for stability in the process mean, for example, to estimating a changing process mean and the resulting prediction error. A typical approach, when the source of the auto-correlation can't be removed or engineering process control used, is to track the level of the process using a time series model. Unusual shocks to the process are then detected using a control chart based on the one-step-ahead forecast errors. A brief review of this active area of research is given by Woodall and Faltin (1993). Also see Montgomery and Mastrangelo (1991), Faltin et al. (1997), and Adams and Lin (1998).

Some recent results are given by Mastrangelo (1998) on monitoring with multivariate, autocorrelated variables. This emerging area is likely to be challenging technically, but useful in many practical applications. This may prove to be an area in which latent structure methods can be successfully applied.

VARIABLE SAMPLING METHODS

A considerable amount of work has been done on methods which allow varying sample sizes and varying sampling intervals based on information as it is obtained from the process. For example, if it appears that a process is drifting from target, then the next sample is taken sooner or the sample size for the next sample is increased. Allowing for variable sample size and/or sampling intervals allows for quicker detection of process shifts, although it increases the administrative complexity of the monitoring scheme. For an introduction to these ideas, the reader is referred to Reynolds, Amin, and Arnold (1990); Costa (1997); Crowder et al. (1997); Zimmer, Montgomery, and Runger (1998); and Tagaras (1998).

ECONOMIC DESIGN METHODS

There have been and continue to be many papers appearing on the economic design of control charts based on ideas originally proposed by Duncan (1956). With economic models, various costs are assigned to sampling, non-conforming parts, repairs, and so forth. Also a number of time-oriented parameters must be specified, such as the average time until the process shifts to a given out-of-control condition, the time required for sampling, and the time required to investigate a false alarm. Once the input parameters are specified, the sample size, sampling interval, and decision rule are determined using optimization techniques to minimize the expected cost. Recent reviews of this area are given by Ho and Case (1994) and Keats et al. (1997). A critique of the economic design approach is given by Woodall (1987). Economic approaches to the design of attribute charts are referenced in the bibliography by Woodall (1997). Because economically designed charts can have poor statistical properties and are, in general, incapable of detecting process improvements, the use of statistical constraints is recommended, as proposed by Saniga (1989).

CHANGE-POINT ESTIMATION

Some readers may recognize a similarity in the purpose of control charting and that of change-point estimation. In change-point estimation the focus is usually on estimating the time at which a change in the process occurred once the change has been detected. Control charting has typically been focused more on detecting such a change as quickly as possible after it occurs. Obviously, the two areas are related, and there has been some recent work combining them. See, for example, Yashchin (1997) and Samuel, Pignatiello, and Calvin (1998). For a review of change-point methods, see Zacks (1991). Change-point methods also have a Phase I/Phase II distinction, as does control charting.

ENGINEERING PROCESS CONTROL AND SPC

The SPC goal of controlling a process to target with minimal variability is shared with engineering feed-forward and feedback control. A number of researchers have studied how engineering process control and SPC can be combined to take advantage of the strengths of each (see, e.g., MacGregor (1987); Vander Wiel et al. (1992); Montgomery et al. (1994); Box and Luceño (1997); and Box, Coleman, and Baxley (1997)). This research area is closely tied to the study of control charting with autocorrelated data.

NONPARAMETRIC APPROACHES

There are a number of nonparametric approaches to control charting; see Bakir (1998) and Chakraborti, Van der Laan and Bakir (1999) for reviews. Some recent approaches are studied by Pappanastos and Adams (1996), Willemain and Runger (1996), and Jones and Woodall (1998). There would appear to be an increasing role for non-parametric methods, particularly as data availability increases. Abundant data would cause the loss of power associated with nonparametric methods to become less of an issue. Nonparametric methods would seem especially useful in the multivariate case in which an assumption of multivariate normality is required for most methods proposed thus far. Several nonparametric multivariate methods have already been proposed, for example, by Ajmani, Randles, and Vining (1998) and Chang and Fricker (1998).

GENERAL TRENDS AND RESEARCH IDEAS

Several research ideas arose from the Journal of Quality Technology (JQT) panel discussion edited by Montgomery and Woodall (1997). Some of these are incorporated into the list of trends and ideas in this section. The reader is also referred to Montgomery (1992), Kolesar (1993), and MacGregor (1997) for additional ideas and perspectives.

i. Most SPC methods have been developed and modified over the years to maximize the information obtained from relatively scarce data. Now in industry there is often an overwhelmingly large amount of data. Thus, SPC methods are needed for massive data sets. Some work on this topic is reported by Runger et al. (1997) and Yashchin (1998). We would expect nonparametric methods to be particularly useful in this data-rich environment. Also, it may be necessary to desensitize standard methods in the presence of a large amount of data to prevent detection of very small instabilities of no practical importance.

ii. The scope of SPC should be broadened to include a much wider variety of methods for understanding variation over time, not just traditional control charting. Multi-step production processes and measurement processes should be considered. Some work has been done in this direction, but much more is needed. See, for example, Hawkins (1991). The study of the transmission of variation through the process is important as discussed recently by Lawless (1998) and Fong and Lawless (1998). In the current manufacturing environment, multiple measurements are often made on each manufactured unit at multiple times during production. Methods are needed to take full advantage of this information. In auto making, for example, it may then be easier to trace the source of a defect found in final inspection to a root cause early in the assembly process. Palm et al. (1997) refer to this capability as traceability and consider it a major step forward in the application of SPC.

iii. Most of the research on SPC methods has been focused on monitoring the process mean (or mean vector). Process variability is just as, or more, important. There has been a trend toward more research on monitoring process variability, but more work is needed on this topic. The multivariate case, in particular, has received relatively little attention although some recent results are reported by Tang and Barnett (1996a, 1996b). Also, much of the early work on monitoring process variability did not address the detection of decreases in variability, that is, process improvement.

iv. It has already been mentioned that more research is needed on the effect of parameter estimation on control chart performance.

v. Given the difficulties associated with interpreting signals from multivariate control charts, more work is needed on graphical methods for data visualization. Data reduction methods are also important.

vi. Industry has been moving away from the use of attribute data toward the use of continuous measurements. Variables data enables tighter control of processes with smaller sample sizes. Still, there are some open research topics involving attribute data, as listed by Woodall (1997).

vii. The trend in the economic modeling and design of control charts is to incorporate statistical constraints. The development of an economic model which incorporates process improvement as well as quality deterioration would be a major advance.

viii. It is very likely that there are many results in the change-point literature which could be applied to SPC problems. A greater synthesis of these two areas is needed. There has already been some movement in this direction, but we expect much more.

ix. There are review papers needed on topics such as the effect of parameter estimation on control chart performance. Review papers tend to spark new research ideas.

x. Since many new methods are unlikely to be used unless computer programs are available, there is an opportunity to program existing methods. Some journals (e.g., JQT) publish computer programs.

xi. There is an opportunity for cross-fertilization of ideas from other areas of statistical science, for example, epidemiology, outlier detection, and even economics and finance (see for example, Stoumbos (1999)).

xii. There is a need for publication of case studies illustrating the benefits of SQC. This presents an opportunity for those in academia to work with those in various industries. Practitioners have the applications and data but rarely the time and motivation to publish case studies.

xiii. A number of mathematical statisticians have worked on process monitoring topics (see, for example, Lai (1995)). Work is needed to make the most useful mathematical results more accessible to quality practitioners.

RELEVANCE AND ACCEPTANCE OF RESEARCH RESULTS

Kolesar (1993), Banks (1993), and others have questioned the relevance of much of the research on SPC. Going still further, Gunter (1998), referring to the control chart, stated, "The reality of modern production and service processes has simply transcended the relevance and utility of this honored but ancient tool." Although Gunter (1998) admitted that his opinions were outspoken to stimulate discussion, it is clear from a review of virtually any set of industrial training materials that most of the methods taught are roughly fifty years old. Thus they are not directly suitable for many modern manufacturing environments. Many of the advances in the understanding and use of SPC methods which could increase their relevance and utility have not had a significant impact. 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."

There are several reasons for the considerable gap between the useful theory and actual practice of SPC. Many, if not most, of the users of control charts have had relatively little training in statistics. Thus there is a reluctance to introduce more complex topics, such as the study of autocorrelation, into training materials. Also, changes in SPC practice have been actively discouraged by a number of people, including W. E. Deming, by far the most influential statistician who has worked in the quality area. Finally, many researchers have generally considered their work ended with the publication of their results. There is usually little effort to see the work implemented in practice. If new ideas are implemented in creative and useful ways, the advances are not publicized often enough through case study papers. User-friendly computer applications are rarely developed. In many cases the work is written in such a way that very few industrial practitioners can understand it. Many of the changes in general practice that do occur are due to textbook authors, software developers, and consultants. Thus the time required for useful research to be implemented is much too slow. Unfortunately, some of the new methods which do get promoted are ineffective ones.

Some of the reasons for this unfortunate situation are well-known, but the solutions are not easy ones. In most of academia, research publications lead to promotion, tenure, and pay raises. In many academic departments, the status of a journal is directly related to its level of mathematical complexity. In the view of Box (1990, 1994, and 1995), the use of the mathematical paradigm in statistics is a serious mistake. Often there is little motivation for activities beyond journal publication on any research idea, regardless of its usefulness. Thus some researchers tend to stay focused on narrow subareas without acknowledging that the entire field of study will suffer unless they also work to improve statistical practice. The academic environment is different in industrial engineering, the primary engineering area in which SPC research is done. Here, an important issue is obtaining funding to support research, which often necessitates an argument of relevance for the results. Sometimes work is done cooperatively with industry. Indeed, much of the research done in SPC over the years has been done by those working in industry, often on their own time. In many cases, the problem is not relevance, but the lack of acceptance and integration of new ideas in what could be considered the base of knowledge associated with the term SPC.

As in any area of statistical science, some of the research in SPC is not necessarily immediately and directly applicable to "real-world" processes. Some of it was never intended to be so. In much of academia, the rewards are for publications, not usefulness. Consequently, even though an idea is not directly relevant to practical application, but could lead to publication in a good journal, the idea will typically be pursued. Furthermore, some topics have theoretical and intellectual value, even though their immediate practical application may not be obvious. This certainly does not mean that the research is frivolous and will never be useful. A good example is the theoretical research on alphabetically-optimal experimental designs that started in the 1950's. There were few applications of these ideas in designing real-world experiments until the last 10 years. However today, almost every experimental design software package incorporates D-optimal designs because they are highly useful for experiments with irregular regions (such as mixture experiments), nonstandard models, or unusual blocking requirements. Practitioners use these optimal designs routinely to address these problems. There is certainly a need for a stronger trend toward more relevance in SPC research, but it is even more important that the traditional base of knowledge for SPC practice be expanded to include new methods and ideas.

Much of the influence to increase the relevance of SPC research could come from journal editors and referees. More could be expected of authors regarding the applicability and readability of their results. Practical implementation and examples could be required for publication, as is presently required by JQT and by Technometrics.

Finally, entire areas of research in SPC need to be reassessed from the perspective of their impact on statistical practice. This is never an easy process since no one welcomes criticism of their work. Indeed, the work by one of the authors has been strongly criticized by Banks (1993). Some researchers believe, though, that there has been more research on economic design of control charts than is justified by practical applications. In his criticism of the relevance of much of the SPC research, Kolesar (1993) seems to be referring primarily to economic modeling. One could argue that if the area of economic design of control charts has not had a significant impact on statistical practice in forty years of development, then perhaps it is time to concentrate research efforts elsewhere. Economic design consists of sophisticated methods for designing simple tools. The changing manufacturing environment, on the other hand, calls for simple methods for designing more complex tools. As a rough estimate, about 20% of the research effort in SPC has been devoted to economic design methods. On the other hand, cost is a language that appeals to management, so measuring the impact of an SPC system or procedure in economic terms might be helpful in attracting management support and other resources to implement an entire set of quality improvement activities. Also, economic modeling of control charts brought many individuals from the operations research and engineering communities into the SPC field and fostered other collaboration of these researchers with statisticians. So while there has been little direct application of much of the research results, it is difficult to characterize the work as without value.

CONCLUSIONS

This paper is meant to serve only as an introduction to some research directions, opportunities, and issues in the area of SPC. For a more detailed technical discussion, the reader is referred to the JQT panel discussion edited by Montgomery and Woodall (1997). This panel discussion includes the views of a number of the leading researchers and practitioners in the SPC area. Montgomery (1992), Gibra (1975), and Vance (1983) provide earlier views of research on SPC. For a general introduction, the textbooks by Montgomery (1996) and Ryan (2000) are recommended. They contain many up-to-date references. Also, see Woodall and Adams (1998).

The reader is encouraged to consider doing research in the SPC area. In one respect the authors disagree strongly with Deming (1993, p. 180), who stated, "The Shewhart control charts do a good job under a wide range of conditions. No one has yet wrought improvement." In our view while Shewhart charts are widely useful, many important advances have been made and the SPC area offers some exciting areas of research. There are many important, unanswered questions still to be addressed. Although the contributions of Shewhart, Deming, and others have been fundamental in nature and monumental in effect, the process of statistical monitoring and control can benefit, like any process, from continuous improvement. SPC methods must be adapted to a changing manufacturing environment, which now includes trends towards shorter production runs, more data, higher quality requirements, and greater computing capability.

ADDED MATERIAL

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