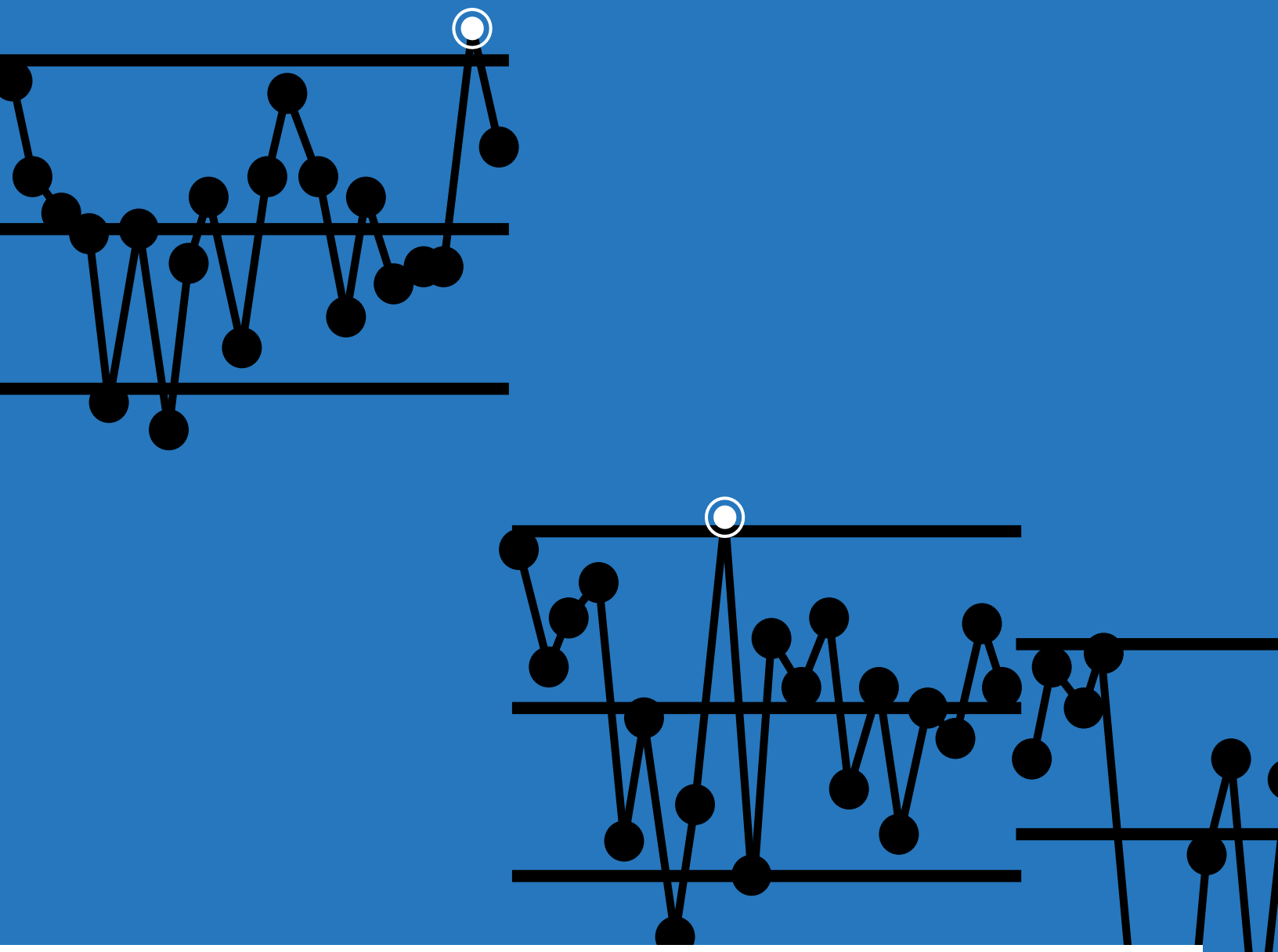


jmp STATISTICAL DISCOVERY

WHITE PAPER

On 100 Years of the Shewhart Control Chart

William H. Woodall
Virginia Tech

Table of contents

Introduction	1
Walter A. Shewhart	3
The importance of Phase I study of baseline process data	8
The use of more than one variance component	10
Practical importance vs. statistical significance	12
The use of covariates	13
Data aggregation issues	14
Multivariate methods	15
Some application areas other than manufacturing	16
Comments on Industry 4.0	17
Final thoughts	18
References	19

Introduction

My entry into the quality field was simply a matter of my good fortune. My 1980 dissertation at Virginia Tech was on Abraham Wald's sequential probability ratio test. The following year, as an assistant professor at Mississippi State University, I happened upon Zacks' (1981) article on the cumulative sum control chart while browsing through journals in the campus library. I saw where the mathematics used in my dissertation could be applied to study quality monitoring methods. Unbeknownst to me at the time, the United States was in the midst of the quality revolution, motivated by competition with Japanese companies, with widespread interest in the use of statistical methods to monitor and improve quality. I have spent much of the last forty years working in the statistical process monitoring area, frequently with co-authors and graduate students, and have benefited greatly from the ideas of Walter Shewhart.

My goal in writing this white paper is to commemorate the 100th anniversary of the control chart. I also give the readers some food for thought and perhaps some ideas on how to make fuller use of their control charts. I give some practical advice, some of it well-worn, on how one might achieve the best results in implementing statistical process monitoring. Additional details can be found in the paper by Zwetsloot et al. (2023).

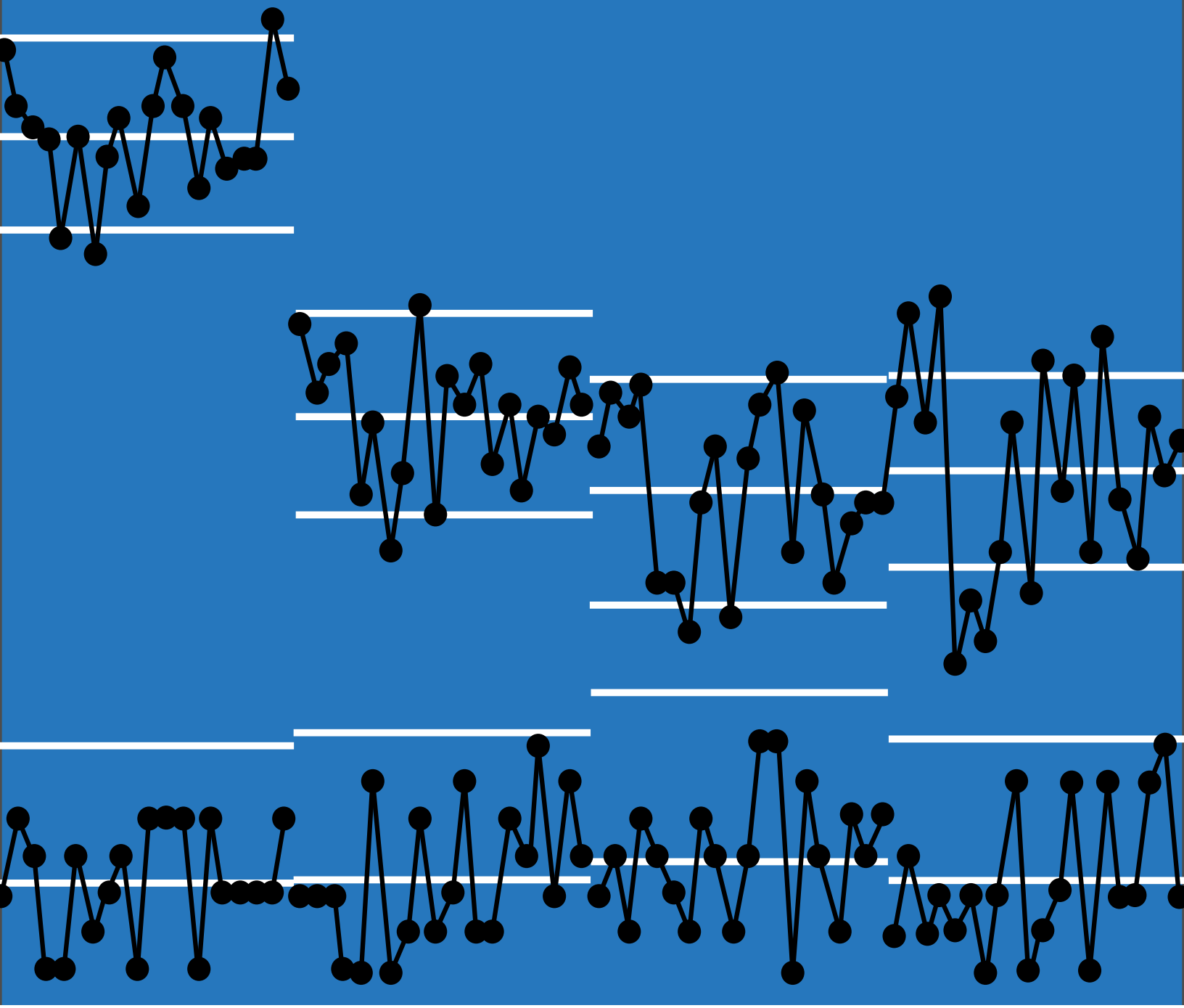
Some references are given for more information on the various topics. I also think it is important to give credit to some of the originators of the various ideas. There are many topics that aren't covered and my remarks are, of course, limited by my own experience and interests. Many individuals have contributed to the advancement of the theory and application of statistical process monitoring. I apologize to those to whom I do not give proper credit. I would be happy to correspond with anyone who is interested in more information or who wishes to provide feedback.

For more information on statistical methods for process monitoring, quality improvement, and variation reduction, I recommend the books shown in Figure 1 by Wheeler and Chambers (2010), Steiner and MacKay (2005), and Montgomery (2020), with the latter paired with the JMP Companion by Ramirez and Ramirez (2018).



Figure 1: Useful books on statistical quality control

Walter A. Shewhart



Walter A. Shewhart

Walter A. Shewhart (1891-1967), pictured in Figure 2, is considered the "father of statistical quality control." He spent his professional career at the Western Electric Company (1918-1924) and then as a member of the technical staff at Bell Laboratories (1925-1956). Many biographical articles have been written about his life. In particular, the August 1967 issue of the journal *Industrial Quality Control* was a special memorial issue published in his honor. The tributes published in it show the high level to which he was appreciated, respected, and even beloved.

Shewhart thought broadly about the use of statistics in industry, promoted the ideas of operational definitions and rational subgrouping, and wrote extensively about the concept of randomness. My focus, however, is on the impact and extensions of his control chart, which made its first appearance in Shewhart's 1924 memorandum (reproduced in Figure 3). He was one of the first to recognize the informational value in maintaining the time order of industrial data. The value of considering time order is common knowledge now, but the previous practice had been to aggregate data over time into one sample, thus losing the information contained in the time order.

Shewhart had a huge influence on statistical practice internationally, not just in the United States. Mahalanobis (1948) and Pearson (1967) reviewed his influence on statistical applications in India and the UK, respectively. Shewhart never visited Japan, but his work was very influential there. As reviewed by Kolesar (1994), W. Edwards Deming (pictured in Figure 4) championed the use of the control chart during his 1950 lectures in Japan. Control chart methods were taught earlier in Japan by Homer M. Sarasohn, who published very forward-thinking books on statistical quality control (Sarasohn, 1951) and industrial management (Sarasohn and Protzman, 1949). These books were published in Japanese and recently translated into English. Sarasohn's colleague, C. B. Protzman, had been a senior production manager at AT&T and thus likely to have been influenced by Shewhart's ideas.

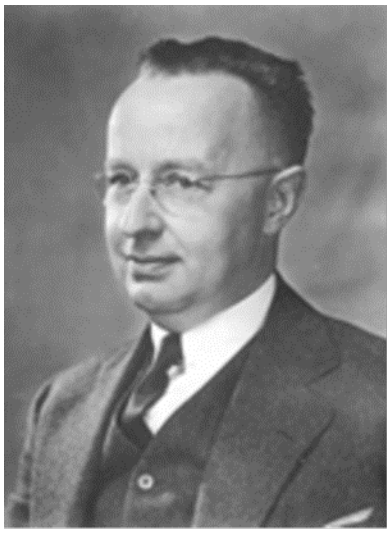


Figure 2: Photo of Walter A. Shewhart

The First Shewhart Control Chart

Case 1801)

WAS-724-5-16-24-FQ

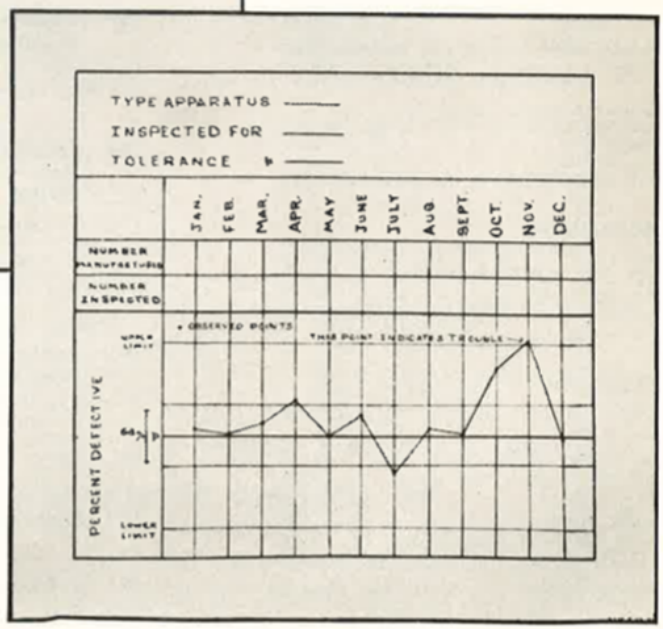
MR. R. L. JONES:-

A few days ago, you mentioned some of the problems connected with the development of an acceptable form of inspection report which might be modified from time to time, in order to give at a glance the greatest amount of accurate information.

The attached form of report is designed to indicate whether or not the observed variations in the percent of defective apparatus of a given type are significant; that is, to indicate whether or not the product is satisfactory. The theory underlying the method of determining the significance of the variations in the value of p is somewhat involved when considered in such a form as to cover practically all types of problems. I have already started the preparation of a series of memoranda covering these points in detail. Should it be found desirable, however, to make use of this form of chart in any of the studies now being conducted within the Inspection Department, it will be possible to indicate the method to be followed in the particular examples.

W. A. SHEWHART.

Enc.:
Form of Report.



72 August 1967 Industrial Quality Control

Figure 3: The original Shewhart control chart (Reprinted with permission from ASQ© 1967 ASQ. www.asq.org)



Figure 4: W. Edwards Deming (Photo courtesy of The W. Edwards Deming Institute®)

Ishikawa (1967) wrote the following as part of his tribute to Shewhart:

> This control chart method and the concepts of Dr. Shewhart had great influence upon Japanese industry and since then have had great effect on popularization of statistical quality control in Japan and on the improvement of Japanese products.

J. M. Juran visited Japan in 1954; his lectures focused mostly on quality management issues (Kolesar, 2008). Juran downplayed somewhat the role of statistics in quality improvement, but wrote in 1997 that the control chart was an invention that many would have loved to have invented, including himself. The contributions of Shewhart, Deming and Juran to the quality field have been widely recognized, and deservedly so, but in my view Sarasohn's contributions have been underappreciated.

Shewhart had leadership roles in a number of statistical organizations. He was, for example, President of the American Statistical Association (1945) and served twice as President of the Institute of Mathematical Statistics (1937, 1944). He was a founding member of the American Society for Quality Control (now the American Society for Quality).

The goal in manufacturing is to keep the process quality characteristics centered on target values with minimal variation. Shewhart proposed the control chart for plotting time-ordered data to distinguish between expected (common cause) variation and unusual (assignable cause) variation. This information leads to process understanding and improvement opportunities without overreacting to what is considered to be normal process variation. The idea is to remove assignable causes, if possible, in order to reduce variation. Changes to the process could potentially lead to the reduction of common cause variation. Steiner et al. (2023) discussed these issues in considerable detail.

Shewhart's articles and his 1931 and 1939 books contain a lot of practical advice, but much of his philosophical discussion is notoriously difficult to understand. W. Edwards Deming, who actively promoted Shewhart's ideas, wrote the following in 1968:

Although Dr. Shewhart's explanations could be simple and clear in face-to-face discussion, his greatest papers remain as difficult for the reader as they were for the writer. As he told me once, when he writes, he must make it fool-proof. I replied in a particular instance that he had made it so fool-proof that no one would understand it. This was not just a joke: there was truth in it.

One should be wary of anyone who claims a full understanding of Shewhart's writing. Quotes can, and have been, cherry-picked to support either side of arguments over topics such as the role of the normal distribution in process monitoring and

the relationship between control charting and hypothesis testing. Some of the disagreements were discussed by Woodall (2000). For a wealth of practical advice on the implementation of Shewhart's ideas in practice, I recommend the Western Electric Handbook (1956).

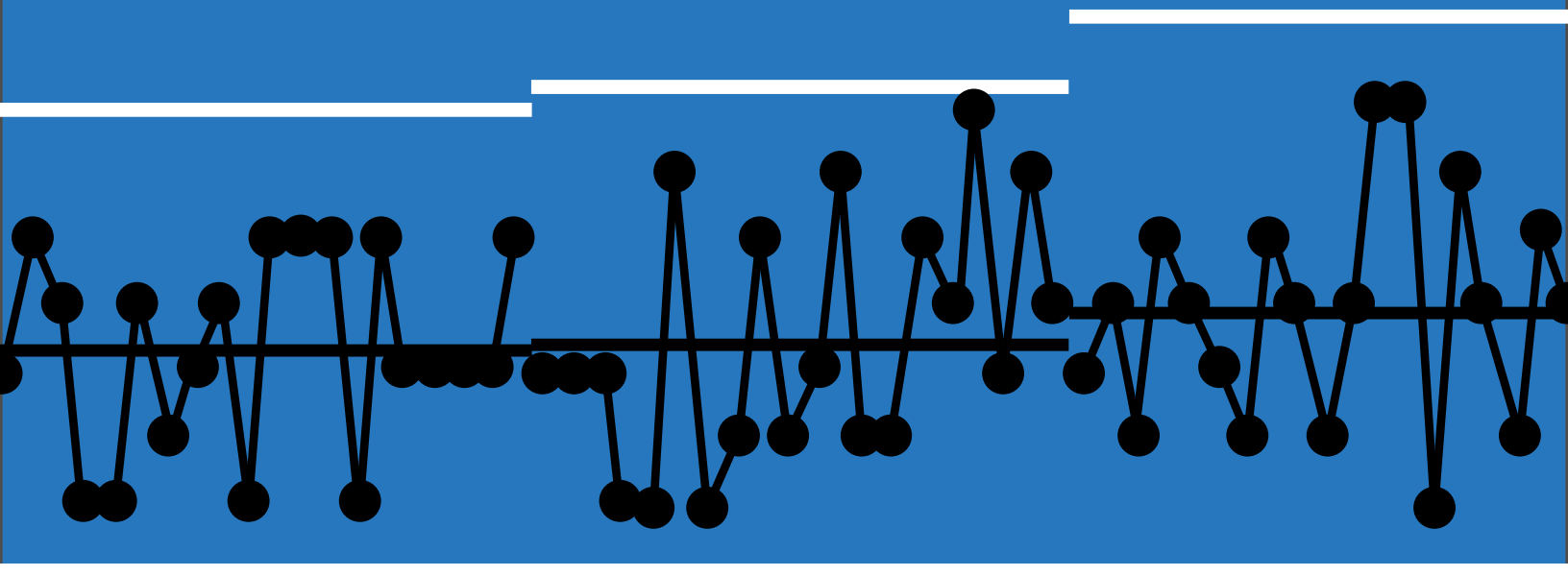
Shewhart's X-bar and R charts for monitoring the mean and standard deviation, respectively, of important quality characteristics remain the most commonly used methods in practice for monitoring variables data. In almost all cases, the control limits are set at plus and minus three standard errors of the plotted statistic, i.e., "three-sigma" limits are used. It is common to use runs rules with the Shewhart charts, e.g., signaling an out-of-control situation if two out of the most recent three plotted values fall beyond the same two-sigma limits. The probability of false alarms increases, however, as runs rules are added. In the case of individual data values, it is typically recommended that the moving range method be used to estimate the process standard deviation.

Shewhart invented the control chart in the Industry 2.0 era, the time period from 1900 to 1970, when measurements were taken manually and data were scarce. Data storage consisted of writing values on a worksheet and drawing the chart on accompanying graph paper. An example of these worksheets and the graph paper can be found in the Western Electric Handbook (1956, pp. 210-211). Thankfully, with the use of computer software, these activities are relics of the past.

Deming (1993, p. 180) wrote, "The Shewhart control charts do a good job under a wide range of conditions. No one has yet wrought improvement." As data became more plentiful in the Industry 3.0 era (from 1970 to 2011), and software such as JMP became available, the basic Shewhart chart was modified in various ways, however, to handle the changes in the volume and structure of the data. As discussed below, modifications of the basic Shewhart charts became necessary in situations in which there are, for example, more than one common cause variance component, excess capability, important covariates, or autocorrelation.

Toward the end of this paper, I make a few comments on the situation in our current Industry 4.0 era (2011-present) where the volume, velocity, and variety of data being collected can be overwhelming.

The importance of Phase I study of baseline process data



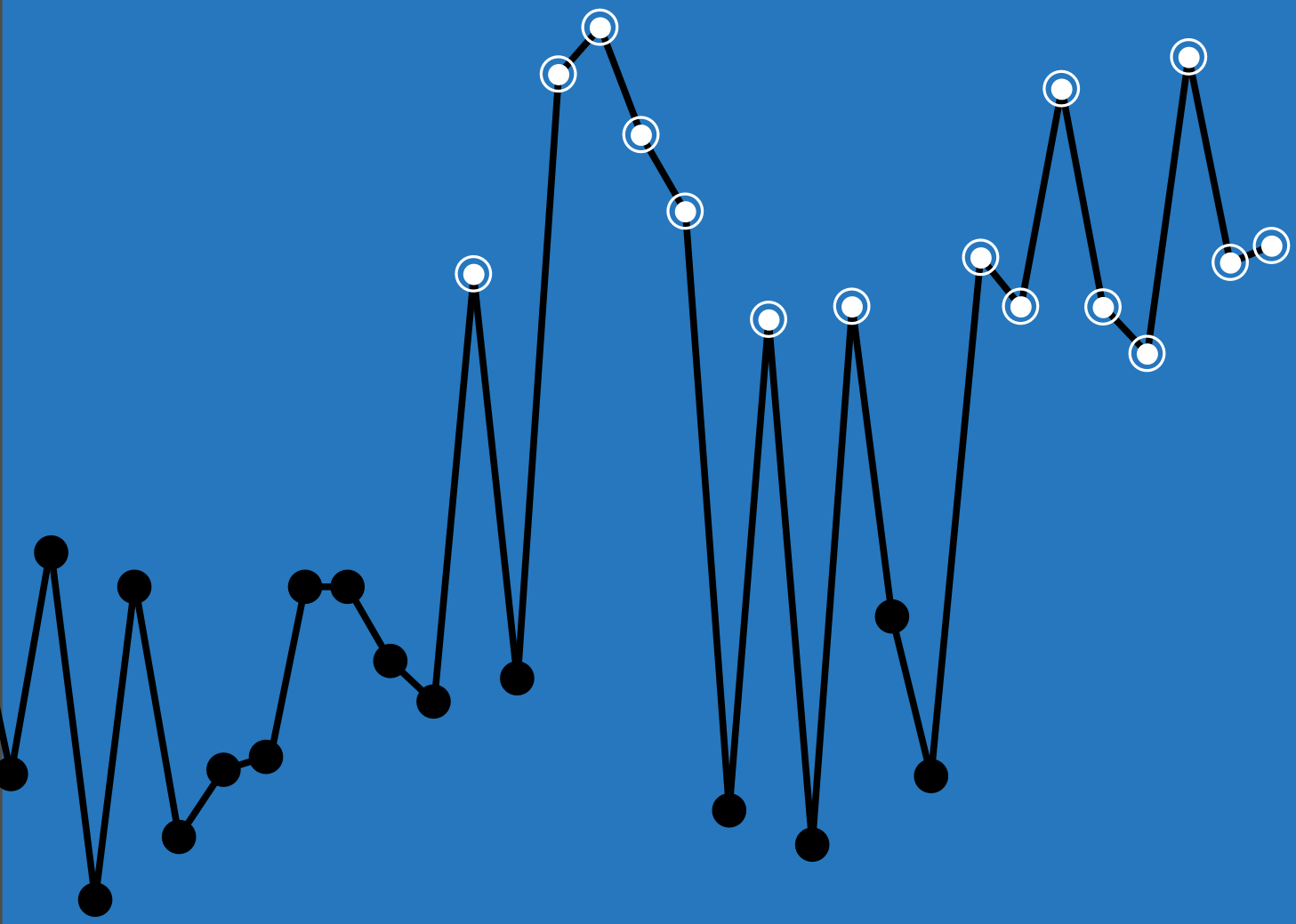
The importance of Phase I study of baseline process data

The importance of collecting and analyzing historical data to establish a baseline, in what has been referred to as Phase I, is almost always underemphasized, especially in the research literature. Shewhart focused almost entirely on Phase I process improvement applications, although he recognized the importance of maintaining an ongoing record in what is now referred to as Phase II. Variation reduction and other process improvement projects recognized as needed after examining process data often require additional data collection. MacKay and Steiner (1997) and Steiner and MacKay (2005) discussed a number of variation reduction strategies that one can use to identify dominant sources of variation and then either eliminate them or account for their effects.

Jones-Farmer et al. (2014) discussed some of the most important guidelines and decisions related to Phase I. Most of the knowledge about the process is obtained in examining the Phase I data. One should not expect to observe stability of the process in Phase I. One should try to identify clues for process improvement that could lead to improved performance and stability. The model, sampling strategy, and control chart required for any ongoing monitoring in Phase II are typically end products of the Phase I study. In manufacturing applications, Phase I is followed by a capability analysis.

It is important to avoid any probability distribution tests or assumptions until the process is stable. Some textbooks and popular software packages (not JMP, by the way) lead one to believe that normality is required before a control chart can be plotted and advise a Box-Cox transformation of the data as the initial step. This advice puts the cart well before the horse. Stability must come first. As Deming (1986, 312) wrote, probability distributions "serve no useful purpose for improvement of a process unless the data were produced in a state of statistical control." Khakifirooz et al. (2021) showed that using the Box-Cox transformation can mask even extreme outliers, effectively defeating the purpose of using the control chart. Generally, as Wheeler (2009) also argued, nonlinear transformations of the data should be used sparingly, if at all.

The use of more than one variance component



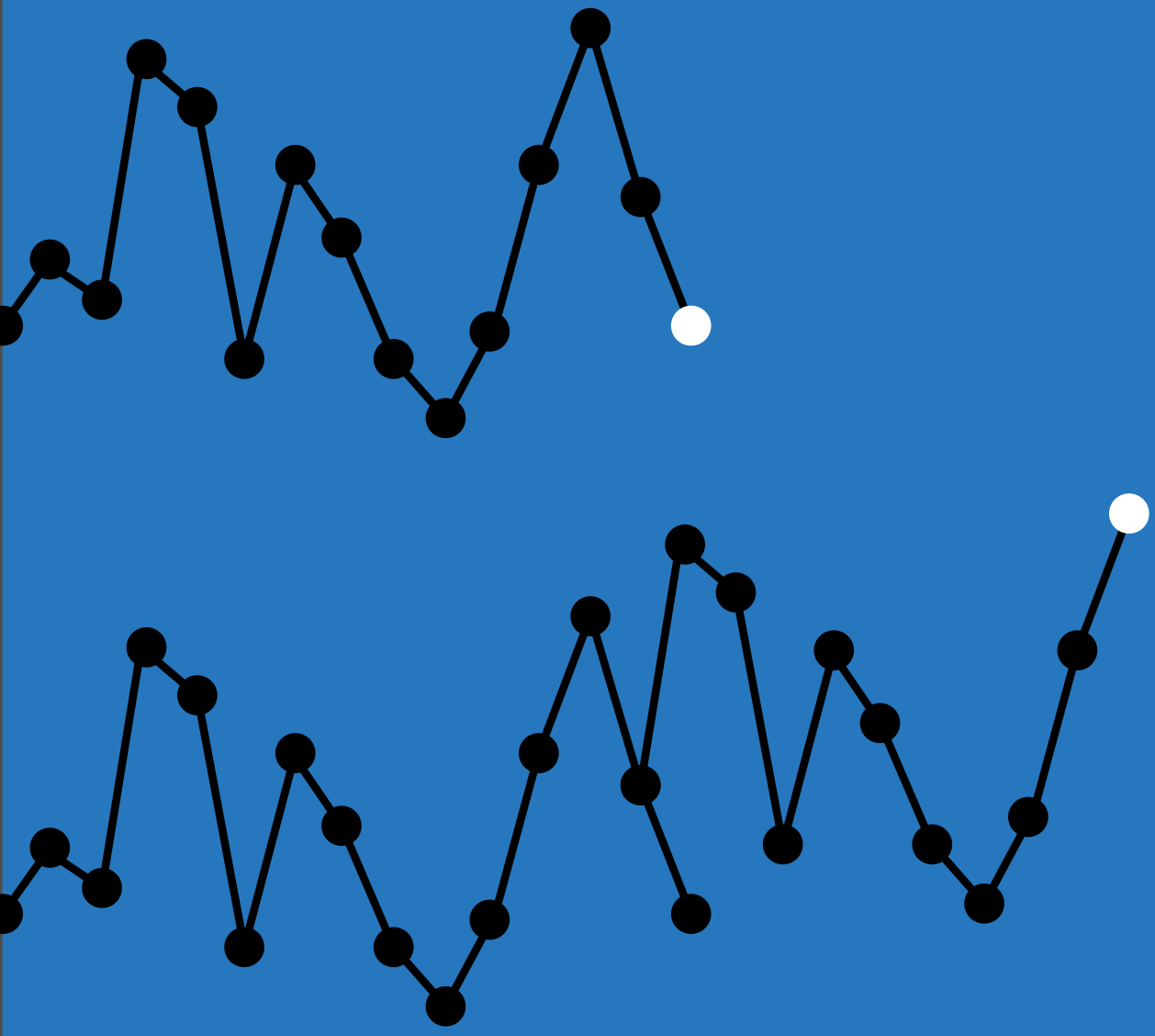
The use of more than one variance component

The Shewhart charts for variables data allow for the incorporation of only one variance component to represent common cause variation. In some applications, there are two components of common cause variation, e.g., when there is "legitimate" batch-to-batch variation and variation within the batches. If standard methods are used, then there will be many signals from the X-bar chart, indicating what one already knows, i.e., there is variation between the batches. It is recommended in this situation to use three charts, an individuals chart for the sample means, with the accompanying moving range chart, and a chart for monitoring the variation within batches. It is possible, but rarer, to have three or more sources of common cause variation. For more information on this topic with respect to variables data, see Yashchin (1994) and Woodall and Thomas (1995).

One can have common cause variation between subgroups when monitoring proportion or count data as well. This situation becomes more of an issue when sample sizes are very large, allowing even small differences over time in an underlying proportion to be detected. This issue was recognized in the Western Electric Handbook (1956, pp. 196-197), where it was recommended to use an individuals chart based on the sample proportions with control limits based on the average moving range when the sample sizes are in the hundreds or thousands. Laney (2002) recommended an approach based on standardizing the sample proportions and then using the average moving range to estimate the variation. This method can work well in some situations, but fail in others. Somewhat surprisingly, Laney's assumption that the successive standardized sample proportions have the same variance does not hold. These issues were discussed by Goedhart and Woodall (2022).

It is important to keep in mind that using additional variance components is only appropriate when all of the variance components represent common cause variation, otherwise these methods can mask the presence of process shifts and informative outliers. This point also applies when using a beta-binomial model for monitoring a proportion instead of a binomial model or using the gamma-Poisson model instead of the Poisson model when monitoring count data.

Practical importance vs. statistical significance



Practical importance vs. statistical significance

Control charts issue signals that result from the statistical significance of the data as compared to the baseline established in Phase I. As we know, statistical significance does not imply practical significance, which is especially problematic when sample sizes are large. In an increasing number of cases, it is important to ensure the practical significance of alarms.

Freund (1960), who worked for Kodak, wrote:

> Many assignable causes produce effects that are real, but small and unimportant. In fact, it is often completely uneconomical to detect these effects, much less worry about how to correct them.

Freund held that some slack can be allowed in the value of the process mean when working with highly capable processes. His acceptance control chart was a Shewhart chart with widened or "modified" limits.

Indeed, Shewhart (1939, p. 30) seemed to agree with Freund at least somewhat, writing,

> An assignable cause of variation as this term is used in quality control work is one that can be found by experiment without costing more than it is worth to find it.

Even in the Western Electric Handbook (1956, p. 193) one finds, "In many cases there is an area or 'band' of acceptable levels within which the engineer is willing to let the process run."

Deming (1982), however, strongly advised against the use of modified limits, even writing "Modified limits, never" in his index. Wheeler (1995, p.346) also advised against modified limits, saying that they are "contrary to continual improvement." I once agreed with their views, but no longer do. As more and more variables are being monitored, it becomes increasingly important to prioritize quality problems and focus on the processes that require the most attention. Sall (2019) discussed how to prioritize process issues when there could be thousands of process data streams. Woodall and Faltin (2019) and Woodall et al. (2022) discussed the practical significance issue in more detail and provided a historical overview.

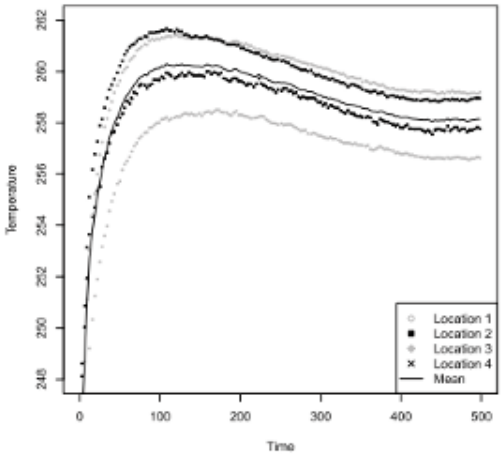
The use of covariates

The basic control charts are based solely on quality variables and do not take advantage of any variables that are correlated with the quality variables. My first exposure to the importance of incorporating covariate information into process monitoring was through Zhang's (1984) cause-selecting chart. With these charts, regression models are used to model the process output variable to account for variation in the corresponding process input variable. This enables one to determine whether an unusual output value is due to a process problem or due to an unusual input variable value. Lawless et al. (1999) gave several examples in automotive manufacturing in which the input dimensional measurement before a manufacturing step was highly correlated to the measurement made after the step.

More information on the cause-selecting chart was provided by Wade and Woodall (1994). Zhang's cause-selecting chart can be viewed as the basic building block for more complicated multistage monitoring methods and variation transmission studies, topics discussed by Shi (2006).

There are other approaches that combine regression analysis with process monitoring. Mandel (1969), for example, used his regression control chart to monitor the number of postal worker hours required over successive four-week periods by taking into account the mail volume. One plots the time-ordered residuals on the regression control chart. Ignoring the covariate in such a situation can lead to misleading or unhelpful results. Many of the examples in the literature on regression control charts involve only one or two covariates, but there is no limit on the number of covariates that could be used or on the type of model employed.

Regression control charts involve fitting a model and monitoring the residuals. If one collects enough data at each sampling time to refit the model, then one can monitor the model (or function) itself. This approach is referred to as profile monitoring, where one monitors the relationship between the quality variable and one or more explanatory variables. One of the first applications, discussed by Croarkin and Varner (1982), was the monitoring of linear calibration curves at the U.S. National Bureau of Standards. An example of an oven temperature profile from the case study paper by Jensen et al. (2016) is shown in Figure 4, where the temperature varies over time and over oven location.



There have been hundreds of papers written on profile monitoring since the review paper by Woodall et al. (2004) was published. The profile monitoring approach is useful when the quality of a product or process is best described by a function and interest is in detecting changes in the functional relationship. Extensions have been made to methods for monitoring images, shapes, and surfaces.

Figure 5: Raw data plot of oven temperature nonlinear profiles for four oven locations and the mean profile as a solid line. From Jensen et al. (2016). Reprinted with permission from Taylor & Francis Ltd. http://www.tandfonline.com

Data aggregation issues

In his 1924 chart, Shewhart plotted the percentages of defective products with the data aggregated over months. Shewhart advised the aggregation of variables data over time into small subgroups, typically of size four. Shewhart (1939, p. 32-33) wrote:

> ...emphasis always has been and must be laid upon breaking up the original sequence into subgroups of comparatively small size. If this is not done, the presence of assignable causes will very often be overlooked.
>
> By using large subgroups we tend to get overlappings of the effects of different assignable causes and the effects of a single cause are masked.

These quotes get to the heart of the matter. Some aggregation can remove noise and make patterns clearer, but too much aggregation results in a harmful loss of information. With respect to Shewhart's 1924 chart shown in Figure 3, it would have perhaps been useful to drill down into the data to see if the quality problem identified in November could be associated with a particular day of the week or a particular shift. It is important to identify the root cause of quality problems.

In my view, the use of aggregation of the data has not received enough attention. In the research literature, it is frequently implicitly assumed that samples of data values can be collected instantaneously. This assumption seems unrealistic. In practice, it would be more common to collect samples by aggregating data over time. Zwetsloot and Woodall (2021) reviewed some of the work that has been done on the topic of aggregation and some practical considerations.

The effect of autocorrelation

As sampling frequencies increase, data tend to become positively autocorrelated due to the presence of inertial effects. Measurements made closer in time tend to be closer in value. In addition, there are often seasonal effects with public health-related data. If standard control chart methods are used with positively autocorrelated data, there will be many potentially misleading out-of-control signals. Alwan and Roberts (1988) were not the first to study this issue, but they brought the issue to the forefront. They recommended fitting a time series model to the data, plotting the forecasted values on a chart with engineering-based decision limits, and plotting the one-step-ahead forecast errors on a control chart in order to identify unusual shocks to the system.

Before taking the approach of Alwan and Roberts (1988), one should try to remove the source of the autocorrelation, thus reducing the variation in the quality characteristic, or consider the use of feedback control as illustrated by MacGregor (1990) and Box and Narasimhan (2010).

Multivariate methods

Hotelling (1947) proposed the first control chart for monitoring two or more correlated quality variables. Data points can be unusual outliers in the multivariate sense by violating the correlational structure, while not unusual when plotted on the corresponding univariate charts. Much has been written about multivariate control charts and many have been proposed. As evidence of the interest, the review paper on multivariate monitoring methods by Bersimis et al. (2007) is the most cited paper in *Quality and Reliability Engineering International*.

Multivariate charts can be useful, but there are some issues and limitations associated with the basic charts. As the number of variables increases, the power to detect process mean vector shifts of a given size decreases, estimating the variance-covariance matrix becomes more difficult, and interpreting any out-of-control signal becomes more challenging. In addition, the variables being monitored must be collected at the same sampling frequency. In many instances, the multivariate normal distribution is assumed, an assumption that is likely to be violated in many applications. Multivariate methods have proven useful, however, in monitoring the parameters of parametric models of profile data.

Supplemental use of Shewhart control limits

Shewhart's ideas gave rise to a variety of process monitoring methods. These include the cumulative sum (CUSUM) chart proposed by Page (1954) and the exponentially weighted moving average (EWMA) chart proposed by Roberts (1959). The Shewhart chart is a special case of the CUSUM chart when the decision boundary is set to zero and a special case of the EWMA chart when the smoothing parameter is set to one. Hawkins and Olwell (1998) thoroughly covered the CUSUM methods, whereas Lucas and Saccucci (1990) provided useful information on EWMA charts.

The CUSUM and EWMA charts can be designed to more quickly detect small and moderate sustained shifts in the mean, as measured in units of the standard error, than with use of the Shewhart chart. The Shewhart chart is better, however, at detecting larger shifts and isolated outliers. To combine the best of these methods, it is recommended that Shewhart limits be used in conjunction with the CUSUM or the EWMA chart.

Some application areas other than manufacturing

Shewhart's ideas have spread well beyond manufacturing. There is an increasing number of application areas for statistical process monitoring.

My interests have included healthcare applications and public health surveillance. A considerable amount of work has been done since the review by Woodall (2006) was published. Riley et al. (2021), for example, recently reported on the successful use of control charts in the British National Health Service. Healthcare applications frequently involve the analysis of count data, such as the rate of infections, or waiting time data.

Much of our work in recent years has been on the monitoring of surgical outcome data that requires risk-adjustment to account for differences in the ages, gender, and health conditions of the surgical patients. Most often a logistic regression model is used to predict the probabilities that patients will suffer a given adverse event within a specified number of days following surgery and CUSUM charts for monitoring. An example from Novik et al. (2006) is shown in Figure 6. The upper CUSUM plot is designed to detect deterioration in surgical performance, while the lower plot is designed to detect process improvement. Woodall et al. (2015) and Sachlas et al. (2019) provided reviews of papers on surgical outcome monitoring.

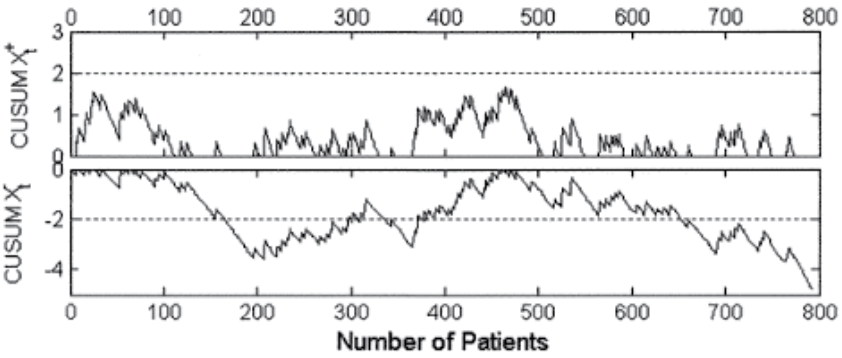


Figure 6: Risk-adjusted CUSUM analysis of a surgeon's adverse outcome rate. From Novick et al. (2006). Reprinted with permission from Elsevier.

Unkel et al. (2012) wrote in their review of many approaches that the methods of statistical process control have a long history of application to problems in public health surveillance where spatiotemporal data play a central role.

Another application of recent interest is in the monitoring of social network data. This challenging area involves monitoring large sparse square matrices containing Bernoulli or count data. The dimensions of the matrices correspond to the number of individuals in the network. Stevens et al. (2021) discussed the connections between network monitoring and statistical process monitoring.

Control charts have also proven useful in other areas such as in environmental monitoring, as discussed by Arciszewski (2023), and in financial surveillance (see Frisén, 2008 and Bisiotis et al., 2022).

Comments on Industry 4.0

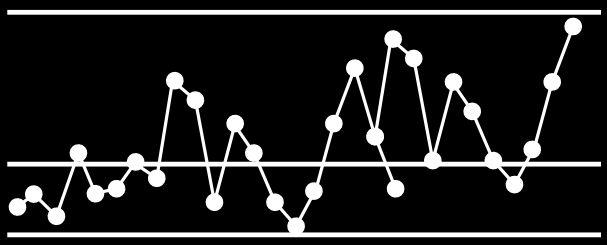
Industry 4.0 technology encompasses cyber-physical manufacturing systems, additive manufacturing, the use of digital twins, machine learning, and the use of the Internet of Things. In manufacturing applications, there are frequently many data streams resulting from the widespread use of sensor technology. There could be millions of observations on thousands of variables. The data streams are often autocorrelated and cross-correlated, with dimension reduction methods often recommended. Sampling frequencies can be high with important variables measured at different frequencies. Multistage data can take a variety of forms, e.g., as scalars, counts, functions, or images. Process understanding and monitoring can thus become quite difficult. Diagnostic and control methods are needed in conjunction with the monitoring. Many companies have found that it is easier to collect data than to figure out how to extract meaningful information from them.

In a case study, Beauchemin and Ramsey (2020) discussed the use of JMP software in accessing, extracting, and formatting Industry 4.0 data. Although many of the Industry 3.0 monitoring methods can remain useful, new and considerably more sophisticated statistical approaches are required. Quite a bit has been written about alternative approaches for the monitoring of manufacturing data. One example is the approach of Ferrer (2019), who advocated the use of latent structure-based multivariate statistical process control methods used in chemical engineering as efficient quality improvement tools in massive data contexts.

Reis and Gins (2017) provided key insights into the evolution of industrial process monitoring. In addition, Zonnenshain and Kenett (2020) provided an interesting perspective on what they called Quality 4.0.

Qiu (2020) discussed the use of statistical process control in a number of big data applications.

Final thoughts



Shewhart's ideas and methods have had a far-reaching, continuing effect. I have discussed some of the useful modifications to his basic chart that have been made over the last century. Other topics were covered by Woodall and Montgomery (2014).

Shewhart was forward thinking. His Plan-Do-Check-Act (PDCA) cycle was a precursor to the popular Six Sigma Define-Measure-Analyze-Improve-Control (DMAIC) process improvement strategy. Many readers will likely agree with the following quote by Shewhart (1939, p. 49):

> The long-range contribution of statistics depends not so much on getting a lot of highly trained statisticians into industry as it does on creating a statistically minded generation of physicists, chemists, engineers, and others who will in any way have a hand in developing and directing the production process of tomorrow.

It seems important in the Industry 4.0 era to add computer scientists to this list. Shewhart himself was a self-taught statistician with a strong background in physics and mathematics.

References

Alwan, L. C. and Roberts, H. V. (1988). "Time-series Modeling for Statistical Process Control". *Journal of Business & Economic Statistics 6(1),* 87-95.

American Society for Quality Control (ASQC) (1967). "The First Shewhart Control Chart". *Industrial Quality Control* 23(8), 72.

Arciszewski, T. J. (2023). "A Review of Control Charts and Exploring Their Utility for Regional Environmental Monitoring Programs". *Environments* 10(5), 78.

Beauchemin, J., Jr. and Ramsey P. J. (2020). "Industry 4.0 and JMP." Paper presented at JMP Discovery Summit, Munich, Germany.

Bersimis, S., Psarakis, S., and Panaretos, J. (2007). "Multivariate Statistical Process Control Charts: An Overview". *Quality and Reliability Engineering International* 23, 517–543.

Bisiotis, K., Psarakis, S., and Yannacopoulos, A. N. (2022). "Control Charts in Financial Applications: An Overview". *Quality and Reliability Engineering International* 38(3), 1441-1462.

Box, G. and Narasimhan, S. (2010). "Rethinking Statistics for Quality Control". *Quality Engineering* 22(2), 60-72.

Croarkin, C. and Varner, R. (1982). "Measurement Assurance for Dimensional Measurements on Integrated-Circuit Photomasks". NBS Technical Note 1164, U.S. Department of Commerce, Washington, DC.

Deming, W. E. (1968). "Walter A. Shewhart, 1891-1967". *Review of the International Statistical Institute* 36, 372-375.

Deming, W. E. (1986). *Out of the Crisis*. Massachusetts Institute of Technology, Center for Advanced Engineering Study, Cambridge, Mass.

Deming, W. E. (1993). *The New Economics for Industry, Government, and Education.* Massachusetts Institute of Technology, Center for Advanced Engineering Study, Cambridge, Mass.

Ferrer, A. (2014). "Latent Structures-based Multivariate Statistical Process Control: A Paradigm Shift". *Quality Engineering* 26(1), 72-91.

Freund, R. A. (1960). "A Reconsideration of the Variables Control Chart with Special Reference to the Chemical Industries". *Industrial Quality Control* 16 (11), 35–41.

Frisén, M., ed. (2008). *Financial Surveillance*. Hoboken, NJ: John Wiley & Sons, Inc.

Goedhart, R. and Woodall, W.H. (2022). "Monitoring Proportions with Two Components of Common Cause Variation". *Journal of Quality Technology* 54(3), 324-337.

Hawkins, D. M. and Olwell, D. H. (1998). *Cumulative Sum Charts and Charting for Quality Improvement. Springer Science & Business Media.*

Hotelling, H. (1947). "Multivariate Quality Control-Illustrated by the Air Testing of Sample Bombsights". In *Techniques of Statistical Analysis*. eds. C. Eisenhart. M. W. Hastay, and W. A. Wallis, New York: McGraw-Hill. pp. 111-184.

Ishikawa, I. (1967). Contribution to "Tributes to Walter A. Shewhart". *Industrial Quality Control*, August issue, pp. 115-116.

Jensen, W. A., Grimshaw, S. D., and Espen, B. (2016). "Nonlinear Profile Monitoring for Oven-temperature Data". *Journal of Quality Technology* 48(1), 84-97.

Jones-Farmer, L. A., Woodall, W. H., Steiner, S. H., and Champ, C. W. (2014). "An Overview of Phase I Analysis for Process Improvement and Monitoring". *Journal of Quality Technology* 46(3), 265-280.

Juran, J. M. (1997). "Early SQC: A Historical Supplement". *Quality Progress* 30(9), 73-82.

Khakifirooz, M., Tercero-Gómez, V. G. and Woodall, W. H. (2021). "The Role of the Normal Distribution in Statistical Process Monitoring". *Quality Engineering* 33(3), 497–510.

Kolesar, P. J. (1994). "What Deming Told the Japanese in 1950". *Quality Management Journal* 2(1), 9-24.

Kolesar, P. J. (2008). "Juran's Lectures to Japanese Executives in 1954: A Perspective and Some Contemporary Lessons". *Quality Management Journal* 15(3), 7-16.

Laney, D. B. (2002). "Improved Control Charts for Attributes". *Quality Engineering* 14 (4), 531–537.

Lawless, J. F., Mackay, R. J., and Robinson, J. A. (1999). "Analysis of Variation Transmission in Manufacturing Processes – Part I". *Journal of Quality Technology* 31(2), 131-142.

References

Lucas, J. M. and Saccucci, M. S. (1990). "Exponentially Weighted Moving Average Control Schemes: Properties and Enhancements" (with discussion). *Technometrics* 32(1), 1-12.

Mandel, B. J. (1969). "The Regression Control Chart". *Journal of Quality Technology* 1(1), 1-9.

MacGregor, J. F. (1990). "A Different View of the Funnel Experiment". *Journal of Quality Technology* 22(4), 255-259.

MacKay, R. J. and Steiner, S. H. (1997). "Strategies for Variability Reduction". *Quality Engineering* 10(1), 125-136.

Mahalanobis, P. C. (1948). "Walter A. Shewhart and Statistical Quality Control in India". *Sankhyā: The Indian Journal of Statistics* 9(1), 51-60.

Montgomery, D. C. (2020). *Introduction to Statistical Quality Control*, Eighth Edition, John Wiley & Sons, Inc.

Novick, R. J., Fox, S. A., Stitt, L. W., Forbes, T. L., and Steiner, S. (2006). "Direct Comparison of Risk-adjusted and Non–risk-adjusted CUSUM Analyses of Coronary Artery Bypass Surgery Outcomes". *The Journal of Thoracic and Cardiovascular Surgery* 132(2), 386-391. The Journal of Thoracic and Cardiovascular Surgery | ScienceDirect.com by Elsevier

Page, E. S. (1954). "Continuous Inspection Schemes". *Biometrika* 41(1/2), 100–115.

Pearson, E. S. (1967). "Some Notes on WA Shewhart's Influence on the Application of Statistical Methods in Great Britain". *Industrial Quality Control* 24(2), 81-83.

Qiu, P. (2020). "Big Data? Statistical Process Control Can Help!", *The American Statistician*, 74(4) 329-344."

Ramirez, B. S. and Ramírez, J. G. (2018). *Douglas Montgomery's Introduction to Statistical Quality Control: A JMP Companion*. SAS Institute.

Reis, M. S. and Gins, G. (2017). "Industrial Process Monitoring in the Big Data/Industry 4.0 Era: From Detection, to Diagnosis, to Prognosis". *Processes* 5(3), 35.

Riley, S., Burhouse, A., and Nicholas, T. (2021). "National Health Service (NHS) Trust Boards Adopt Statistical Process Control Reporting: The Impact of the Making Data Count Training Programme". *BMJ Leader*.

Roberts, S. W. (1959). "Control Chart Tests Based on Geometric Moving Averages". *Technometrics* 1, 239–250.

Sachlas, A., Bersimis, S., and Psarakis, S. (2019). "Risk-adjusted Control Charts: Theory, Methods, and Applications in Health". *Statistics in Biosciences* 11, 630-658.

Sall, J. (2018). "Scaling-up Process Characterization". *Quality Engineering* 30(1), 62–78.

Sarasohn, H. M. (1951). *The Road to Quality Control: The Industrial Application of Statistical Quality Control*, Kagaku Shinko Sha, translated into English in 2019 by N. I. Fisher and Y. Tanaka with essay by W. H, Woodall. Hoboken, NJ: John Wiley & Sons.

Sarasohn, H. M. and Protzman, C. B. (1949). *The Fundamentals of Industrial Management*. Civil Communications Section, GHQ, SCAP.

Shewhart, W. A. (1931). *Economic Control of Quality of Manufactured Product*. Macmillan and Co. Ltd, London.

Shewhart, W. A. (1939). *Statistical Method from the Viewpoint of Quality Control*. Washington, DC: Graduate School of the Department of Agriculture (Republished in 1986 by Dover Publications, Inc., Mineola, NY).

Shi, J. (2006). *Stream of Variation Modeling and Analysis for Multistage Manufacturing Processes*. CRC Press.

Steiner, S. H. and MacKay, R. J. (2005). *Statistical Engineering*. Quality Press.

Steiner, S. H., Stevens, N. T., and MacKay, R. J. (2023). "Statistical Process Control/Monitoring: A View on the Fundamental Definitions and Terminology". Presented at the XIVth International Workshop on Intelligent Statistical Quality Control, Washington, DC.

Stevens, N.T., Wilson, J.D., Driscoll, A.R., McCulloh, I., Michailidis, G., Paris, C., Parker, P., Paynabar, K., Perry, M.B., Reisi-Gahrooei, M. and Sengupta, S. (2021). "Research in Network Monitoring: Connections with SPM and New Directions". *Quality Engineering* 33(4), 736-748.

Unkel, S., Farrington, C. P., Garthwaite, P. H., Robertson, C., and Andrews, N. (2012). "Statistical Methods for the Prospective Detection of Infectious Disease Outbreaks: A Review". *Journal of the Royal Statistical Society Series A: Statistics in Society* 175(1), 49-82.

Wade, M. R. and Woodall, W. H. (1993), "A Review and Analysis of Cause-Selecting Control Charts". *Journal of Quality Technology* 25(3), 161-169.

References

Western Electric Company (1956). *Statistical Quality Control Handbook*. Western Electric Corporation, Indianapolis, IN.

Wheeler, D. J. and Chambers, D. S. (2010). *Understanding Statistical Process Control.* Third edition. SPC Press, Knoxville, TN.

Wheeler, D. J. (1995). *Advanced Topics in Statistical Process Control* (Vol. 470). SPC Press, Knoxville, TN.

Wheeler, D. J. (2009). "Transforming the Data Can be Fatal to Your Analysis". Quality Digest. https://www.qualitydigest.com/inside/healthcare-column/transforming-data-can-befatal-your-analysis-090309.html.

Woodall, W. H. (2000). "Controversies and Contradictions in Statistical Process Control" (with discussion). *Journal of Quality Technology* 32(4), 341-378.

Woodall, W. H. (2006). "Use of Control Charts in Health-Care and Public-Health Surveillance" (with discussion). *Journal of Quality Technology* 38(2), 89-104.

Woodall, W. H. and Faltin, F. W. (2019). "Rethinking Control Chart Design and Evaluation". *Quality Engineering* 31(4), 596-605.

Woodall, W. H., Faltin, F. W. and Yashchin, E. (2022). "The Importance of Tuning Your Control Charts". *Quality Progress* 55(9), 28-35.

Woodall, W. H., Fogel, S. L., and Steiner, S. H. (2015). "The Monitoring and Improvement of Surgical Outcome Quality". *Journal of Quality Technology* 47(4), 383-399.

Woodall, W. H. and Montgomery, D. C. (2014). "Some Current Directions in the Theory and Application of Statistical Process Monitoring". *Journal of Quality Technology* 46(1), 78-94.

Woodall, W. H., Spitzner, D. J., Montgomery, D. C., and Gupta, S. (2004). "Using Control Charts to Monitor Process and Product Quality Profiles". *Journal of Quality Technology* 36(3), 309-320. (Corrigendum, JQT 2006, 38(2), 197.)

Woodall, W. H. and Thomas, E.V. (1995). "Statistical Process Control with Several Components of Common Cause Variability". *IIE Transactions* 27(6), 757-764.

Yashchin, E. (1994). "Monitoring Variance Components". *Technometrics* 36(4), 379-393.

Zacks, S. (1981). "The Probability Distribution and the Expected Value of a Stopping Variable Associated with One-sided CUSUM Procedures for Non-negative Integer-valued Random Variables". *Communications in Statistics-Theory and Methods* 10(21), 2245-2258.

Zhang, G. X. (1984). "A New Type of Control Charts and a Theory of Diagnosis with Control Charts". *World Quality Congress Transactions.* American Society for Quality Control. pp. 175-185.

Zonnenshain, A., and Kenett, R. S. (2020). "Quality 4.0 – The Challenging Future of Quality Engineering". *Quality Engineering* 32(4), 614-626.

Zwetsloot, I. M. and Woodall, W. H. (2021). "A Review of Some Sampling and Aggregation Strategies for Basic Statistical Process Monitoring" (with discussion). *Journal of Quality Technology* 53(1), 1-16.

Zwetsloot, I. M., Jones-Farmer, L. A., and Woodall, W. H. (2023). "Monitoring Univariate Processes using Control Charts: Some Practical Issues and Advice". To appear in *Quality Engineering.*



jmp.com

JMP and all other JMP Statistical Discovery LLC product or service names are registered trademarks or trademarks of JMP Statistical Discovery LLC in the USA and other countries. ® indicates USA registration. Other brand and product names are trademarks of their respective companies. Copyright © 2023 JMP Statistical Discovery LLC. All rights reserved.