Welcome to 2018 and what I hope will be a prosperous year for all. First off, I want to thank you for your continued membership in the Statistics Division. I’ve been a member of the division since almost its inception and have had the privilege of being part of the division leadership team these past ten years. It is now an honor to be the Chair of the Statistics Division this year. I humbly follow in the footsteps of those past chairs who blazed the trail ahead of me and created such a strong foundation.

One of my most enjoyable roles has been that of Outreach Chair where the goal is to promote our division’s products and services at different conferences. Many people come up to our booth and comment that they want to learn more about statistical methods because they are doing “stats” at work. To that end, one of our most popular giveaways has been a SPC Reference Card that captures many of formulas, factors, etc. necessary to construct a wide range of control charts. Often people ask if they can grab a handful for officemates. This year we will be exploring what other reference card can we produce to help promote statistical knowledge.

One of our more popular offerings these past few years has been the webinars that we sponsor. They have ranged from the introductory level to the advanced level. As a professional society, our goal should be to have a majority of members certified in their chosen area of interest. While I was Chair of the Voice of the Customer Committee, we found that members with at least one certification are more satisfied with ASQ overall and tend to stay with the Society longer. To that end, Adam Pintar (Past Chair and current webinar coordinator) along with myself are on a mission to create a series of webinars that will help members prepare for the Certified Quality Engineer exam. The CQE Body of Knowledge encompasses more than just statistics so we are working with other divisions to lend their expertise in this effort.

The ASQ World Conference on Quality Improvement will be in Seattle this spring and our Fall Technical Conference will be in Florida this fall. I hope to see you on one coast if not the other this year.
Submission Guidelines

Mini-Paper
Interesting topics pertaining to the field of statistics should be understandable by non-statisticians with some statistical knowledge. Length: 1,500-4,000 words.

Feature
Focus should be on a statistical concept; can either be of a practical nature or a topic that would be of interest to practitioners who apply statistics. Length: 1,000-3,000 words.

General Information
Authors should have a conceptual understanding of the topic and should be willing to answer questions relating to the article through the newsletter. Authors do not have to be members of the Statistics Division. Submissions may be made at any time to newsletter@asqstatdiv.org.

All articles will be reviewed. The editor reserves discretionary right in determination of which articles are published. Submissions should not be overly controversial. Confirmation of receipt will be provided within one week of receipt of the email. Authors will receive feedback within two months. Acceptance of articles does not imply any agreement that a given article will be published.

Disclaimer
The technical content of material published in the ASQ Statistics Division Newsletter may not have been refereed to the same extent as the rigorous refereeing that is undergone for publication in Technometrics or J.Q.T. The objective of this newsletter is to be a forum for new ideas and to be open to differing points of view. The editor will strive to review all articles and to ask other statistics professionals to provide reviews of all content of this newsletter. We encourage readers with differing points of view to write to the editor and an opportunity to present their views via a letter to the editor. The views expressed in material published in this newsletter represents the views of the author of the material, and may or may not represent the official views of the Statistics Division of ASQ.

The Statistics Division was formed in 1979 and today it consists of both statisticians and others who practice statistics as part of their profession. The division has a rich history, with many thought leaders in the field contributing their time to develop materials, serve as members of the leadership council, or both. Would you like to be a part of the Statistics Divisions’ continuing history? Feel free to contact chair@asqstatdiv.org for information or to see what opportunities are available. No statistical knowledge is required, but a passion for statistics is expected.

Vision
The ASQ Statistics Division promotes innovation and excellence in the application and evolution of statistics to improve quality and performance.

Mission
The ASQ Statistics Division supports members in fulfilling their professional needs and aspirations in the application of statistics and development of techniques to improve quality and performance.

Strategies

1. Address core educational needs of members
   - Assess member needs
   - Develop a “base-level knowledge of statistics” curriculum
   - Promote statistical engineering
   - Publish featured articles, special publications, and webinars

2. Build community and increase awareness by using diverse and effective communications
   - Webinars
   - Newsletters
   - Body of Knowledge
   - Web site
   - Blog
   - Social Media (LinkedIn)
   - Conference presentations (Fall Technical Conference, WCQI, etc.)
   - Short courses
   - Mailings

3. Foster leadership opportunities throughout our membership and recognize leaders
   - Advertise leadership opportunities/positions
   - Invitations to participate in upcoming activities
   - Student grants and scholarships
   - Awards (e.g. Youden, Nelson, Hunter, and Bisgaard)
   - Recruit, retain and advance members (e.g., Senior and Fellow status)

4. Establish and Leverage Alliances
   - ASQ Sections and other Divisions
   - Non-ASQ (e.g. ASA)
   - CQE Certification
   - Standards
   - Outreach (professional and social)

Updated October 19, 2013
Past Chair’s Message

Richard Herb McGrath

Many things happened during 2017. The United States experienced multiple hurricanes and wildfires. The political scene was, let’s say, interesting. But in the Statistics Division, things went smoothly thanks to the efforts of our member leaders. As always, we had a booth at the WCQI and got to see old friends and make some new ones. As we have for years, we co-sponsored the Fall Technical Conference which was held in Philadelphia this year. The next FTC will be in Florida in October and we hope you can make it there. We held several free webinars (thanks for organizing them Adam!) and will continue to do so this year. We continue to publish this Statistics Digest three times per year with very useful technical content arranged by Matt Barsalou (thanks Matt!)

In my previous Chair’s messages, I mentioned the formation of our Data Science and Analytics Technical Committee. In December we finalized the mission and goals. The mission is “To support and promote the use of data science and analytics within the quality profession.” Through this committee we plan to provide speakers for our webinar series as well as at conferences. We hope to form a LinkedIn group to communicate with members. Look for more information in an E-zine and on our website. If you are interested in participating, just send me an email at rmmcgra@bgsu.edu.

So 2017 was a productive year for the Division. I know 2018 will be even better with Steve Schuelka taking over as Chair. Steve will be working with the great group of volunteer leaders that continue to give their time selflessly to the Division. Thanks to all and I wish you a successful 2018!

Editor’s Corner

Matt Barsalou

Welcome to the first 2018 issue of Statistics Digest! Steven Schuelka will be taking over from Richard “Herb” McGrath as Division Chair. I’d like to thank Herb for his service and welcome Steven to the role of Chair. There have also been changes here at Statistics Digest. Alex Gutman, my Technical Reviewer, is moving on and taking the role of Division Treasurer. I am personally grateful to Alex for all the support and assistance he has provided me. I’m pleased to introduce Kurtis Schuler, who will be taking over as Technical Review. Kurtis is a fourth year graduate student pursing a PhD in applied mathematics and statistics at UC Santa Cruz. He has experience in statistical modeling in aerospace and healthcare industries and has also worked in quality assurance for a leading satellite imaging provider.

This issue includes a Mini-Paper by Lynne B. Hare, and a feature by Richard D. Shainin. There are also columns by Bradley Jones and Douglas Montgomery, Donald J. Wheeler, Jack B. ReVelle, Jim Frost, and Mark Johnson. The Youden Address will be published in a later edition. Unfortunately, this issue contains an obituary for John Ramberg, who was Chair of the Statistics Division from July 1983 to June 1984.
PVR and How the Cookie Crumbles

Lynne B. Hare

Introduction

Without calling on the services of big name quality consultants or quality gurus, we have successfully launched what, for many, is a new technology, namely Process Variation Reduction (PVR). Many might view PVR as the same old quality improvement effort, couched differently. But it does indeed have some new twists. The greatest among them is that PVR assembles many well-known tools into a cohesive discipline useful for driving up both productivity and quality. PVR is financially motivated. It examines the whole process (avoiding sub-optimization), and it focuses on the identification of sources of variation and the quantification of this variation by taking the right amount of the right kind of data. These three key elements, process, variation and data, should be familiar to quality practitioners because they form the foundation of Statistical Thinking. While Statistical Thinking and PVR apply across most aspects of corporate business, the most immediate applications are in manufacturing. Still, the principles have been used to great success in research and in sales.

Why is PVR Important?

When process variation is reduced, two things happen, and they are both good. The first is that throughput increases. This means less scrap and rework and fewer line stoppages. It also means greater predictability of production output: instead of producing 10,000 plus or minus 1,000, you’ll produce 11,000 plus or minus 500. Such improvements in planning efficiencies drive dollars to the bottom line. They also make bosses happier, improving the quality of our individual work-life!

The second thing that happens as a result of variation reduction is that quality improves. This means that the consumer’s second experience with the product is more like the first. Such consistency builds consumer trust and contributes to repeat sales. When consumers buy more of our products, we get to stay in business which means we keep our jobs. This builds security at home, increasing the quality of home-life.

Because PVR improves both work-life and home-life, I submit that it is good for us all, both professionally and personally. It works to the universal benefit of humankind; it might even restore hair.

What is PVR?

PVR is a technological derivative of Statistical Thinking motivated by finances and by the desire to make processes of all kinds run more efficiently. The approach used is shown in the flow diagram in Figure 1.

The activity in Box 1 is usually done in cooperation with the finance component. Unlike quality initiatives of the past, and very much like Six Sigma initiatives, PVR is very financially motivated. Experience has shown that it is successful only when it is carried out with the enthusiastic support of the organization’s financial component.
As Yogi Berra said, “You can observe a lot just by watching.” Our second step is to stand and watch. We watch the behavior of the workers and the way the product runs on the lines. We watch for hours and only then draw a process flow diagram, Box 2.

In Box 3, we work to make certain that we have sufficient understanding of the process and its key measurements to make them useful for improvement. This means understanding measurement precision and accuracy and assuring that calibrations are carried out correctly. When such assurances are not present, PVR efforts are in vain because the measurement variation can exceed the manufacturing variation or the measurements can be so biased as to indicate improper action. We also work to assure that we have the key process indicators; that is, measurements of the factors necessary for performance excellence such as measures of first run yield, scrap and rework, and rate of throughput.

Our next step, Box 4, is to mark the flow diagram with comments indicating the kinds and/or sources of variation that might enter the process at each stage. This information will be used later as we seek to minimize overall process variation.

Box 5 represents a tricky step. While we want to stop the financial hemorrhaging at the location in the flow diagram where it is greatest, sometimes, quite often in fact, the cause of difficulties that appear at a particular location in the process is upstream of the point where they are manifest. So plans for data collection, Box 6, must be made with this in mind. It is important to note that the deliberations on all aspects of the process are made by a team of people who are very familiar with the process. This team includes subject matter experts, and their role is key. PVR cannot be carried out by statisticians or quality engineers acting alone.
Boxes 7 and 8 represent the data analysis and interpretation stages. The purpose of data collection and analysis is to learn the difference between what is and what could be. That is, we examine the total process variation and separate it into three component parts. They are common cause, structural and assignable cause variation. The process capability, the variation the process would exhibit if the angels ran it, is an estimate of the size of the common cause variation; if the distribution is normal, the intrinsic capability can be represented as target plus or minus 3 capability standard deviations. Structural variation is that which is due to differences among parallel parts of the process. Such things as parallel production lanes and multiple heads on a filling machine contribute to it. Assignable cause variation is variation imposed on the process by sources outside the process; e.g., raw material variation, variation in environmental factors, shift changes, unnecessary adjustments. Customers experience the composite effect of common, structural and assignable cause variation. This we call process performance. Again, if the distribution is normal, performance is measured by plus or minus 3 performance standard deviations around the target. A large difference between performance and capability indicates productivity and quality improvement opportunities. The Figure 2 is intended to illustrate these concepts.

![Understanding Sources of Variation](image)

While data analysis techniques are very important, graphing the data is essential for both understanding and communication. The visual display of data is always more informative than the analysis of variance or estimation of components of variation, although we do all of these things. For example, variance components are fundamental to the estimation of the 3 kinds of variation. We have found that graphical displays of various types have served to clear away the clouds of misunderstanding and prompt managers into action toward improvement. Graphical presentation of findings facilitates follow-up studies, Box 9, because managers actually see the improvement potential and are, therefore, willing to invest in efforts designed to learn root causes. These causes are the very obstacles to picking the financial plums that result from variation reduction.

When we are content that we have harvested as many plums as practicality will permit, and only then, we will move on to the next unit operation, Box 10. But our work is not complete until we have instituted a process to hold the gains, once attained, Box 11. These are usually standard SPC tools like Shewhart Charts based on the variance components estimated during the data analysis stages of Boxes 7 and 8. Holding the gains requires less intensive sampling than conducting PVR studies does.
PVR and How the Cookie Crumbles

What is Required?

Most plant managers I’ve met would not hesitate to inform me that the purpose of the manufacturing operation is the production of product, not the execution of one of my silly studies. It can take some real convincing to persuade them that data are useful by-products of the manufacturing process and that their use will (1) not interfere with production and (2) provide information about how to improve. The failure of legacy systems, such as mindless installations of computerized SPC, does not add points to my side of the scoreboard. Yet willing, cooperative, yea even participating plant managers are essential to PVR success. So, too, are cooperative workers.

This will surprise you, but I’ve actually been in manufacturing facilities where production people and quality staff did not get along. The mindset, the cooperation, the data sharing are all essential to success. So is a healthy discontent for the status quo. This is not to suggest that managers and workers should arrive at work angry, but it does mean that people should firmly believe that they can always make things better. Moreover, it should be part of the job’s definition.

Fear of learning should be a thing of the past. While many will say that their worst course ever was statistics, it is important that all see the value of learning basic statistical tools. These are best taught when the application is at hand and the focus is on process, variation and data, the key elements of Statistical Thinking. PVR provides the opportunity to do this.

A multidisciplinary team is essential, as is the input of subject matter experts, in all of the disciplines associated with the product and process.

What is Unique about this Approach?

Nothing. Almost. This approach to productivity and quality improvement is data driven, but so are others. This approach has strong financial component serving as drivers for success. So does Six Sigma. TQM unfortunately seemed to pit quality practitioners against financial types. PVR thrives on ties with the financial experts.

Like some other approaches, this one allows no sacred cows.

Many other approaches seem to rely on top-down leadership. To a certain extent, PVR does, too. But that is not the way we started it. Instead we started small and demonstrated a few big-bucks successes. When some who were concerned about their turf got in the way of PVR initiatives, we went to the top brass and spoke about successes and additional possibilities. Resistance faded. Now, PVR is top down and bottom up driven.

PVR didn’t need outside quality gurus to get started; instead we had evolution followed by revolution.

How has it been Successful?

Contributions to the businesses have taken two forms. One is dollars to the bottom line, and the other is detection of problems. The two, of course, are related, for when problems are detected and their sources are eliminated, dollars rush to the bottom line, causes registered or not. In 1998, when we started small, we would visit a manufacturing facility for a week, get the PVR ball rolling by carrying out snapshot studies, set up longer term studies, then revisit a few months later with results of longer term studies to make recommendations for change. Examination of accounting records within a few months of that would indicate productivity savings of $100,000 to $150,000 for most projects on the first pass. Inside of 2 years there were approximately 20 such efforts. Most of these were made in international manufacturing facilities. Domestically, one project resulted in over $2,000,000 and occupied
MINI-PAPER Continued

PVR and How the Cookie Crumbles

approximately 2 months (elapsed, not total) of one statistician’s time. As this is almost as much as we pay him for a whole year, we felt good about the time investment. Other, smaller projects typically net $150,000 to $200,000 a year.

Alas, there are too few statisticians to go around. So we are training others to lead the PVR effort. When PVR is rolled out fully, savings will move to the bottom line much more quickly.

References


About the Author

Lynne Hare is a consulting statistician emphasizing business process improvement in R&D, Manufacturing and other strategic functions. Serving a large client base, he has helped bring about culture change in Research by accelerating speed to the successful launch of new products and processes and in Manufacturing through the reduction of process variation.

His former positions include the Director of Applied Statistics at Kraft Foods, Chief of Statistical Engineering at the National Institute of Standards and Technology, Director of Technical Services at Unilever, Manager of Statistical Applications there as well, Statistics Group Leader at Hunt-Wesson Foods and Visiting Professor at Rutgers University.

Lynne’s technical expertise includes experimental strategies and design of experiments for Research as well as quality and productivity improvement for Manufacturing. He holds M.S. and Ph.D. degrees from Rutgers University and an A.B. in mathematics from Colorado College.

Lynne is a Fellow of the American Statistical Association and former chairman of its Section on Quality and Productivity and holder of the Gerald J. Hahn Q&P Achievement Award. He is also a Fellow of the American Society for Quality and former chair of its Statistics Division. The ASQ has awarded him the William G. Hunter and Ellis R. Ott Awards for excellence in quality management. Kraft Foods presented him with the Technology Leadership Award for career accomplishments. He writes a column for *Quality Progress* magazine and has numerous publications in technical journals.

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Replicating runs in a designed experiment was strongly advocated by R. A. Fisher, who could be called the father of design of experiments (DOE). Fisher’s work at Rothamstead Experimental Station was applied in agricultural field trials. In such experimentation, replicating all the level combinations in an experimental plan is reasonable and inexpensive. However, in industrial applications replicating the complete set of test runs is generally infeasible due to its expense in time and resources.

A useful alternative to complete replication is to replicate a small fraction of the experimental runs. Doing this allows the data analyst to compute a model independent estimate of the error variance. By contrast, if there are no replicated runs, then the estimate of the error variance based on lack-of-fit degrees of freedom will be biased if the fitted model is incorrect. And, as George Box reminds us, “all models are wrong.” Often, estimates of the error variance based on lack-of-fit degrees of freedom are larger than the true value of this parameter resulting in lowered power for detecting factor effects.

When all the factors are quantitative, a common practice is to replicate a run at the center of the design region. If the base design is orthogonal for the main effects, replicating the center run does not affect this orthogonality, which is desirable. However, multiple replication of center runs does not lower the variance of estimates of the main effects, which is undesirable.

In this article, we compare two approaches for partial replication of a Definitive Screening Design (DSD). A minimum-run DSD for m factors has \(2m + 1\) runs composed of \(m\) foldover pairs and one center run. A DSD has orthogonal main effects and main effects are also orthogonal to all two-factor interactions (2FIs) and pure quadratic effects (QEs). A minimum-run DSD can provide estimates for an intercept, all \(m\) main effects and all \(m\) QEs. Unfortunately, this model exhausts all the degrees of freedom in the design leaving no way to estimate the error variance. Without this estimate, making inferences about the model effects is impossible.

Suppose an engineering team wanted to replicate two runs of a DSD. One natural approach would be to perform three center runs yielding a design with \(2m + 3\) runs. Call this the CP approach. An alternative approach with same number of runs would be to replicate one of the \(m\) foldover pairs. Call this the FREP approach. The remainder of this article provides a statistical comparison of these two approaches for the six-factor DSD with factors A-F. Without loss of generality for the FREP design, we replicate the pair of runs where the first factor A’s value is zero for both runs.

Both approaches provide two degrees of freedom for estimating the error variance. Using these two degrees of freedom only, the power of the CP approach to detect any main effect with a true parameter value that is twice as big as the error standard deviation is 0.865. This is true for all the main effects due to the orthogonality of the design.

The FREP design does not have orthogonal main effects. Factor A is uncorrelated with all the others. But factors B-F have a correlation of \(1/6th\) with all the others except factor A. The power of the FREP approach to detect factor A’s main effect with a true parameter value that is twice as big as the error
standard deviation is 0.865, which is the same power as for the main effects of the CP design. However, for factors B-F, despite their mutual correlation, the power to detect a main effect of the same magnitude rises to 0.891.

For the CP design all the QEs have a correlation of 0.4 with each other. For the FREP design the QE of factor A is uncorrelated with the QE of any other factors. QEs of factors B-F have a correlation of 1/6th with all the others except factor A. The relative standard error of factor A is only 0.82 times the relative standard errors of the QEs of factors B-F. The relative standard error of a parameter estimate is the standard error assuming that the true value of the error variance is one.

For the CP design all the main effects have a relative standard error that is the square root of 1/10th (i.e. 0.316). For the FREP design factor A also has this relative standard error (i.e. 0.316). For factors B-F the relative standard errors are all lower at 0.3.

There are two properties for which the CP design is preferable to the FREP design. Because of the replicated center runs, the intercept is better estimated. However, in screening experiments, the estimate of the intercept is not as important as the estimates of the main effects. Also, the relative standard errors QEs for factors B-F for the CP design are about two percent smaller than the same quantities for the FREP design.

Recommendations
Considering all these comparisons, we recommend using the FREP design over the CP design. Though the main effects of the FREP design are not orthogonal, factors B-F are better estimated than any of the main effects of the CP design.

We also recommend setting factor A to the factor that the engineering team thinks is most likely to exhibit curvature. Such a factor might be identified a priori as one that might suffer from a diminishing marginal effect as the factor’s value increases.
Myth One: It has been said that the data must be normally distributed before they can be placed on a process behavior chart.

In discussing this myth some historical background may be helpful. Walter Shewhart published his “Economic Control of Quality of Manufactured Product” in 1931. When E. S. Pearson read Shewhart’s book he immediately felt that there were gaps in Shewhart’s approach, and so he set out to fill in these perceived gaps. The result was Pearson’s 1935 book entitled “The Application of Statistical Methods to Industrial Standardization and Quality Control.” In this book Pearson wrote on page 34: “Statistical methods and tables are available to test whether the assumption is justified that the variation in a certain measured characteristic may be represented by the Normal curve.”

After reading Pearson’s book, Shewhart gave a series of lectures that W. Edwards Deming edited into Shewhart’s 1939 book, “Statistical Method from the Viewpoint of Quality Control.” In choosing this title Shewhart effectively reversed Pearson’s title to emphasize that his approach solved a real problem rather than being a collection of techniques looking for an application. On page 54 of this book Shewhart wrote: “we are not concerned with the functional form of the universe, but merely with the assumption that a universe exists. [Italics in the original].” Here Shewhart went to the heart of the matter. While Pearson essentially assumed that the use of a probability model would always be justified, Shewhart created a technique to examine this assumption. The question addressed by a process behavior chart is more basic than “What is the shape of the histogram?” or “What is the probability model?” It has to do with whether we can meaningfully use any probability model with our data.

Shewhart then went on to note that having a symmetric, bell-shaped histogram is neither a prerequisite for the use of a process behavior chart, nor is it a consequence of having a predictable process. Figure 1 shows Shewhart’s Figure 9 from the 1931 book. He characterized these data as “at least approximately [in] a state of control.” This skewed histogram is certainly not one that anyone would claim to be “normally distributed.” So, while Shewhart had thoroughly examined this topic in his 1931 book, his approach was so different from traditional statistical thinking that Pearson and countless others (including this author on his first reading) completely missed this crucial point.

![Figure 1: Shewhart’s Figure 9: Variability in Modulus of Rupture of Clear Specimens of Green Sitka Spruce Typical of the Statistical Nature of Physical Properties](image)

To begin to understand how a process behavior chart can be used with all sorts of data we need to begin with a simple equation from page 275 of Shewhart’s 1931 book:

\[ \int_{A}^{B} f(x) \, dx = P \]

Shewhart described two completely different approaches to this equation. The first of these approaches I call the statistical approach since it describes how we approach statistical inference:

1. Choose an appropriate probability model \( f(x) \) to use;
2. Choose some small risk of a false alarm \((1 - P)\) to use;
3. Find the exact critical values \( A \) and \( B \) for \( f(x) \) that correspond to a risk of \((1 - P)\);
4. Then use these critical values in your analysis.

While this approach makes sense when working with functions of the data (i.e. statistics) for which we know the appropriate probability model, it encounters a huge problem when it is applied to the original data themselves. As Shewhart pointed out, we will never have enough data to uniquely identify a specific probability model for the original data. In the mathematical sense all probability models are limiting functions for infinite sequences of random variables. In consequence this means they can never be said to apply to any finite portion of that sequence. This is why any assumption of a probability model for the original data is just that—an assumption that cannot be verified in practice. (While lack-of-fit tests will sometimes allow us to falsify this assumption, they can never verify an assumed probability model.)

So what are we to do when we try to analyze data? Shewhart suggested a different approach for the analysis of original data. Shewhart’s approach to the equation above was:

1. Choose some generic critical values \( A \) and \( B \) for which
2. the risk of a false alarm \((1 - P)\) will be reasonably small
3. regardless of what probability model \( f(x) \) we might choose, and
4. use these generic critical values in your analysis.

This approach changes what is fixed and what is allowed to vary. With the statistical approach the alpha-level is fixed, and the critical values vary to match the specific probability model. With Shewhart’s approach it is the critical values that are fixed (three-sigma limits) and the alpha-level that is allowed to vary. Thus, rather than choosing a fixed value for \( P \), and having to find the specific critical values \( A \) and \( B \) for each and every probability model, \( f(y,n) \), Shewhart chose to use generic values for \( A \) and \( B \) that would result in \( P \) values close to 1.00 regardless of what probability model might apply. This complete reversal of the statistical approach is what makes Shewhart’s approach so hard for those with statistical training to understand.

Once you see the difference in these two approaches you can begin to see why Pearson and others have been concerned with the probability model \( f(x) \), why they have sought to maintain a fixed alpha level \((1 - P)\), and why they have been obsessed with the computation of exact values for \( A \) and \( B \). And more recently, you can see how others have become obsessed with transforming the data to
make the histogram look more like a normal probability model prior to placing them on a process behavior chart. Their presuppositions prevent them from understanding how Shewhart’s choice of generic, fixed-width, three-sigma limits is completely independent of the choice of a probability model. In fact, with the statistical approach, you cannot even get started without a probability model. Hence, as people keep misunderstanding the basis for process behavior charts, they continue to recreate Myth One.

**Myth Two:** It has been said that process behavior charts work because of the central limit theorem.

The central limit theorem was published by Laplace in 1810. This fundamental theorem shows how, regardless of the shape of the histogram of the original data, the histograms of subgroup averages will tend to have a “normal” shape as the subgroup size gets larger. This is illustrated in Figure 3 where the histograms for 1000 subgroup averages are shown for each of three different subgroup sizes for data obtained from two completely different sets of original data. There we see that even though the histograms for the individual values differ, the histograms for the subgroup averages tend to look more alike and become more bell-shaped as the subgroup size increases.

Many statistical techniques that are based on averages utilize the central limit theorem. While we may not know what the histogram for the original data looks like, we can be reasonably sure that the histogram of the subgroup averages may be approximated by a normal distribution. From this point we can then use the statistical approach outlined in the preceding section to carry out our analysis using the subgroup averages.

However, while we have a central limit theorem for subgroup averages, there is no central limit theorem for subgroup ranges. This is illustrated in Figure 4 where we see the histograms of the subgroup ranges obtained from two different sets of original data. Each histogram shows the ranges of 1000 subgroups, for each of three subgroup sizes, obtained from each of the two data sets shown. As the subgroup size increases the histograms for the subgroup ranges become more dissimilar and do not even begin to look bell-shaped.

Therefore, Myth Two has no basis in reality. If the central limit theorem was the foundation for process behavior charts, then the range chart would not work.

Rather, as we saw in the preceding section, Shewhart chose three-sigma limits to use with the process behavior chart simply because, when the data are homogeneous, these limits will bracket virtually all of the histogram regardless of the shape of that histogram. Three-sigma limits are shown on each of the 16 histograms in Figures 3 and 4. There they bracket better than 98 percent of each histogram, leaving less than a 2 percent chance of a false alarm in each case. In practice, as long as \((1–\Phi)\) is known to be small, we do not need to know the exact risk of a false alarm. This means that when we find a point outside the limits of a process behavior chart the odds are very good that the underlying process has changed and we will be justified in taking action. Three-sigma limits provide us with a suitably conservative analysis without requiring a lot of preliminary work. It is this conservative nature of three-sigma limits that eliminates the need to appeal to the central limit theorem to justify the process behavior chart.
Undoubtedly, Myth Two has been one of the greatest barriers to the use of process behavior charts with management data and process-industry data. Whenever data are obtained one-value-per-time-period it will be logical to use subgroups of size one. However, if you believe Myth Two you will feel compelled to average something in order to invoke the blessing of the central limit theorem, and the rationality of your data analysis will be sacrificed to superstition. The conservative nature of three-sigma limits allows you to use the chart for individual values with all sorts of original data without reference to the shape of the histogram.

Myth Three: It has been said that the observations must be independent—data with autocorrelation are inappropriate for process behavior charts.

Again we have an artificial barrier to the use of a process behavior chart which ignores both the nature of real data and the robustness of the process behavior chart technique. Virtually all data coming from a production process will display some amount of autocorrelation. Autocorrelation is simply a measure of the correlation between a time series and itself. A large positive autocorrelation (lag one) simply means that the data display two characteristics: (1) successive values are generally quite similar while (2) values that are far apart can be quite dissimilar. These two properties mean that when the data have a large positive autocorrelation the underlying process will be changing. To illustrate this property I will use the data from Table 2, page 20 of Shewhart’s 1931 book. These data are the measured resistances of insulation material. These data have an autocorrelation of 0.549, which is detectably different from zero (also known as significantly different from zero). While Shewhart organized these data into 51 subgroups of size four and placed them on an average chart, it could be argued that this subgrouping obscures the effects of the autocorrelation upon the chart. To avoid this problem I have placed these 204 data on an XmR chart in Figure 5.
Shewhart found 8 averages outside his limits. We find 14 individual values and 7 moving ranges outside our limits. So both Shewhart’s average chart and our $XmR$ chart tell the same story. This process was not being operated predictably.

As they found the assignable causes and took steps to remove their effects from this process they collected some new data. These data, shown in Figure 6, show no evidence of unpredictable behavior. Notice that the new limits are only 60% as wide as the original limits. By removing the assignable causes of exceptional variation they not only got rid of the process upsets and the extreme values, but they also removed a substantial amount of process variation. The autocorrelation for the data in Figure 6 is 0.091, which is not detectably different from zero.

![Figure 6: $XmR$ Chart for 64 Additional Resistances from Shewhart (1931) Page 20](image)

This example illustrates an important point. Whenever the data have a substantial autocorrelation the underlying process will be changing, and vice-versa, when the process is moving around the data will tend to have an autocorrelation that is detectably different from zero. Thus, autocorrelation is simply one way that the data have of revealing that the underlying process is changing. On the other hand, when the process is operated predictably, the data are unlikely to possess a substantial autocorrelation.

Remember that the purpose of analysis is insight rather than numbers. The process behavior chart is not concerned with creating a model for the data. Neither is it concerned with whether the data fit a specific model. The purpose of a process behavior chart is to use data for making decisions in the real world. When we insist that the data have to be independent we are adding something to Shewhart’s work that Shewhart was careful to avoid. This example from Shewhart’s first book illustrates that process behavior charts have worked with autocorrelated data from the very beginning. Do not let those who do not understand this point keep you from placing your data on a chart because the values might not be independent.

While a complete treatment of the effects of autocorrelation is beyond the scope of this article, the following observation is in order. While it is true that when the autocorrelation gets close to $+1.00$ or $-1.00$ the autocorrelation can have an impact upon the computation of the limits, such autocorrelations will also simultaneously create running records that are easy to interpret at face value. This increased interpretability of the running record will usually provide the insight needed for process improvement and further computations become unnecessary.

**Myth Four:** It has been said that the process must be operating in control before you can place the data on a process behavior chart.

I first encountered this myth when I was refereeing a paper written by a professor of statistics at a land-grant university in the South, which goes to prove my point that even an extensive knowledge of statistics does not guarantee that you will understand Shewhart.

I suspect that the origin of Myth Four is a failure to appreciate that there are correct and incorrect ways of computing the limits for a process behavior chart. (See my article in the June 2017 Statistics...
The most common of the incorrect ways of computing limits consists of using three-standard-deviation limits rather than three-sigma limits. While this approach was identified as incorrect on page 302 of Shewhart’s 1931 book, it is found in virtually every piece of software available today. While three-standard-deviation limits will mimic three-sigma limits whenever the process is operated predictably, they will be severely inflated when the process is being operated unpredictably. Thus, when someone is using the incorrect way of computing the limits, they might come to believe Myth Four.

Of course, as soon as you believe Myth Four you will begin to look for a way to remedy this perceived defect in the technique. Among the absurdities which have been perpetrated in the name of Myth Four are the censoring of the data prior to placing them on the chart (removing the outliers) and the use of two-standard-deviation limits. (As Henry Neave observed in a letter to the Royal Statistical Society, calculating the limits incorrectly and then using the wrong multiplier is an example of how two wrongs still do not make one right.) Needless to say that these, and all other associated manipulations are unnecessary. The express purpose of the process behavior chart is to detect when a process is changing, and to do this we have to be able to get good limits from bad data.

One of my students had just completed the class and was looking at the archival data they had for their cooling water system. He organized these data into daily subgroups of size five and plotted the averages and ranges for the past 24 days to get the graph shown in Figure 7.

![Figure 7: Subgroup Averages and Subgroup Ranges for Cooling Water Pressures](image)

Based on what he saw in Figure 7, Terry decided to use the first half of the data to compute the limits for this chart. When he did this he got the limits shown in Figure 8.

![Figure 8: Terry’s Average and Range Chart for Cooling Water Pressures](image)
The two high points coincided with the short week prior to the Christmas break, and the drop to the lower points coincided with the January start-up. Based on this chart Terry was able to explain why they were spending over $2 million a year on scrap product. With some minor changes they immediately cut the scrap rate by 70 percent, and by the end of the following year they had cut the scrap rate to 10 percent of what it had been by simply operating their processes more consistently.

But why did Terry only use the first 12 days in computing the data? Because he was afraid that the limits would “blow-up” if he used all of the data. Figure 9 shows the chart of Figure 8 with two sets of limits. The limits shown as solid blue lines were computed using the data from all 24 days. The red dashed lines show Terry’s limits.

While the limits do change slightly, the story told by the chart remains the same regardless of which set of limits you use. The purpose of a process behavior chart is to tell the story contained within the data and the limits are simply a means to this end.

Thus, as illustrated by Figure 9, we can compute good limits using bad data. We do not have to wait until the process is “well-behaved” before we compute our limits. The correct computations are robust. And this is why Myth Four is patent nonsense.

Summary
Shewhart's approach to the analysis of data is profoundly different from the statistical approach. This is why people end up with such confusion when they try to “update” Shewhart by attaching bits and pieces from the statistical approach to what Shewhart has already done. As Shewhart provided us with an operational definition of how to get the most out of any process. Nothing extra is needed to make process behavior charts work. We do not need to check for normality or transform the data to make them “more normal.” We do not have to use subgrouped data in order to receive the blessing of the central limit theorem before the chart will work. We do not need to examine our data for autocorrelation. And we do not need to wait until our process is “well-behaved” before computing limits. All such “extras” will just mess you up, get in your way, leave you confused, and keep you from using one of the most powerful data analysis techniques ever invented.
Z-Score

If a normal distribution has a mean ($\mu$) of zero and a standard deviation ($\sigma$) of one, it is referred to as the standard normal distribution. When this is the case, areas under any normal frequency distribution curve can be obtained by performing a change in scale. This change of scale converts the units of measurement from the original (or “x”) scale into standard units, standard scores, or **z-scores**, by means of the formula:

$$z = \frac{x - \mu}{\sigma}$$

In this new z-scale, the value of $z$, i.e., the **z-score**, is the number of standard deviations the corresponding value of $x$ lies above or below the mean of its distribution. Knowing the value of $z$ allows you to determine the area under the normal curve from one point on the “x” scale to another. Because of the unique properties of the normal distribution, i.e., the mean, median and mode have equal values; the area under the curve between any two values of “x” is equal to the probability of this event taking place.

The concept of the **z-score** has been advanced to include special cases of “z,” e.g.: $Z_u$ is a dimensionless index used to measure the location of a process, i.e., its central tendency, relative to its standard deviation and the process upper specification limit (USL). If the process frequency distribution is normal, the value of $Z_u$ can be used to determine the percentage of the area located above the USL.

$Z_l$ is also a dimensionless index used to measure the location of a process, i.e., its central tendency, relative to its standard deviation and the process lower specification limit (LSL). If the process frequency distribution is normal, the value of $Z_l$ can be used to determine the percentage of the area below the LSL.

$Z_{MIN}$ results from a comparison of the $Z_u$ and $Z_l$ values and is the smaller of the two. It is used to calculate $C_{PK}$, the **mean-sensitive Process Capability Index**.

**COLUMN**

Hypothesis Testing

Estimating a Good Sample Size for Your Study

Jim Frost

When you perform hypothesis testing, there is a lot of preplanning you must do before collecting any data. This planning includes identifying the data you will gather, how you will collect it, and how you will measure it among many other details. A crucial part of the planning is determining how much data you need to collect. In this column, I’ll show you how to estimate the sample size for your study.

Before we get to estimating sample size requirements, let’s go over the factors that influence whether a finding is statistically significant. This process will help you see the value of formally going through a power and sample size analysis rather than guessing.
Factors Involved in Statistical Significance

Look at the chart below and identify which study found a real treatment effect and which one didn’t. Within each study, the difference between the treatment group and the control group is the sample estimate of the effect size.

![Chart showing treatment and control groups for two studies.]  

Did either study obtain significant results? The estimated effects in both studies can represent either a real effect or random sample error. You don’t have enough information to make that determination. Hypothesis tests factor in three factors to determine whether results are statistically significant.

- **Effect size:** The larger the effect size, the less likely it is to be random error. It’s clear that Study A exhibits a more substantial effect in the sample—but that’s insufficient by itself.

- **Sample size:** Larger sample sizes allow hypothesis tests to detect smaller effects. If Study B’s sample size is large enough, its more modest effect can be statistically significant.

- **Variability:** When your sample data have greater variability, random sampling error is more likely to produce considerable differences between the experimental groups even when there is no real effect. If the sample data in Study A have sufficient variability, random error might be responsible for the large difference.

Hypothesis testing takes all of this information and uses it to calculate the p-value—which you use to determine statistical significance. The key takeaway is that the statistical significance of any effect depends collectively on the size of the effect, the sample size, and the variability present in the sample data. Consequently, you cannot determine a good sample size in a vacuum because the three factors are intertwined.

**Power of a Hypothesis Test**

Because we’re talking about determining the sample size for a study that has not been performed yet, you need to learn about a fourth consideration—statistical power. Power is the probability that your design will detect an effect that actually exists in the population. For example, if your study has 80% power, it has an 80% chance of detecting an effect that exists. Let this point be a reminder that when you work with samples, nothing is guaranteed! When an effect truly exists, your study might not detect it. The power of the test depends on the other three factors.
Hypothesis Testing

Goals of a Power and Sample Size Analysis

Power and sample size (PSS) analysis involves taking these four considerations, adding process knowledge, and managing tradeoffs to settle on a good design. During this process, you must heavily rely on your process knowledge to provide reasonable estimates of the input values.

PSS analyses help you manage an essential tradeoff. As you increase the sample size, the hypothesis test gains a greater ability to detect small effects. This situation sounds great. However, larger sample sizes cost more money. And, there is a point where an effect becomes so miniscule that it is meaningless in a practical sense.

You do not want to collect a large and expensive sample just so you can detect an effect that is too small to be useful! Nor do you want an underpowered study that has a low probability of detecting an important effect. Your goal is to collect a sample that is large enough to have a good chance of revealing a meaningful effect—but not too large to be wasteful.

As you’ll see in the upcoming examples, the analyst provides the numeric values that correspond to “a good chance” and “meaningful effect.” These values allow you to tailor the analysis to your needs.

All of these details might sound complicated, but a PSS analysis helps you manage them. In fact, going through this procedure forces you to focus on the relevant information. Typically, you specify three of the four factors discussed above and your software calculates the remaining value. For instance, if you specify the smallest effect size that is practically significant, variability, and power, the software calculates the required sample size.

Let’s work through some examples in different scenarios to bring this to life.

2-Sample t-Test PSS Analysis

Suppose we’re conducting a 2-sample t-test to determine which of two materials is stronger. If one type of material is significantly stronger than the other, we’ll use that material in our process. Furthermore, we’ve tested these materials in a pilot study, which provides background knowledge to draw from.

In a PSS analysis, enter the difference of 5, power value of 0.9, and standard deviation of 4 into your statistical software.

**Differences** is often a confusing value to enter. Do not enter your guess for the difference between the two types of material. Instead, use your process knowledge to identify the smallest difference that is still meaningful for your application. In other words, you consider smaller differences to be inconsequential and it would not worthwhile to expend resources to detect them.

By choosing this value carefully, you tailor the experiment so that it has a reasonable chance of detecting useful differences while allowing smaller, non-useful differences to remain potentially undetected. This value helps prevent us from collecting an unnecessarily large sample.

For our example, we’ll enter 5 because smaller differences are unimportant for our process.

**Power values** is where we specify the probability that the test detects the difference if that difference really exists. This field is where you define the “reasonable chance” that I mentioned earlier. If you hold the other input values constant and increase the power of the test, the required sample size also increases. The proper value to enter in this field depends on norms in your industry or company. Common power values are 0.8 and 0.9.

We’ll enter 0.9 so that the 2-sample t-test has a 90% chance of detecting a difference of 5.
**Standard deviation** is the field where we enter the data variability. We need to enter an estimate of the common standard deviation for the strengths of the two types of material. These estimates are typically based on specifications, pilot studies, and historical process data. Inputting better estimates of the variability will produce more reliable PSS results. Consequently, you should strive to improve these estimates over time as you perform additional studies and testing.

For our example, we'll assume that the two types of material have a standard deviation of 5 units of strength. After we click OK, we see the results.

**Interpreting the Power and Sample Size Results**

Power and sample size analyses can provide both numeric and graphical results, as shown below.

### Power and Sample Size

2-Sample t Test

Testing mean 1 = mean 2 (versus ≠)
Calculating power for mean 1 = mean 2 + difference
\( \alpha = 0.05 \) Assumed standard deviation = 4

<table>
<thead>
<tr>
<th>Sample</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference</td>
<td>Size</td>
</tr>
<tr>
<td>5</td>
<td>15</td>
</tr>
</tbody>
</table>

*The sample size is for each group.*

The text output indicates that we need 15 samples per group (total of 30) to have a 90% chance of detecting a difference of 5 units.
Hypothesis Testing

The dot on the Power Curve corresponds to the information in the text output. However, by studying the entire graph, we can learn additional information about how power varies by the difference. If we start at the dot and move down the curve to a difference of 2.5, we learn that the test has a power of approximately 0.4 (40%). This power is too low. However, we indicated that differences less than 5 were not practically significant to our process. Consequently, having low power to detect this difference is not problematic.

Conversely, follow the curve up from the dot and notice how power quickly increases to nearly 100% before we reach a difference of 6. This design satisfies the process requirements while using a manageable sample size of 15 per group.

Other Power and Sample Size Options

Now, let’s explore a few more options that are available for this type of analysis. This time we’ll use a one-tailed test and have the software calculate a value other than sample size.

Suppose we are again comparing the strengths of two types of material. However, in this scenario, we are currently using one kind of material and are considering switching to another. We will change to the new material only if it is stronger than our current material. Again, the smallest difference in strength that is meaningful to our process is 5 units. The standard deviation in this study is now 7. Further, let’s assume that our company uses a standard sample size of 20, and we need approval to increase it to 40. Because the standard deviation (7) is larger than the smallest meaningful difference (5), we might need a larger sample.

In this scenario, the test only needs to determine whether the new material is stronger than the current material. Consequently, we can use a one-tailed test. This type of test provides greater power to determine whether the new material is stronger than the old material, but no power to determine if the current material is stronger than the new—which is acceptable given dictates of the new scenario.

In this analysis, we’ll enter the two potential values for Sample sizes and leave Power values blank. The software will estimate the power of the test for detecting a difference of 5 for designs with both 20 and 40 samples per group.

Enter sample sizes 20 and 40, difference of 7, and standard deviation 7 into your statistical software and perform a two-tailed test with a significance level of 0.5.

Interpreting the Power and Sample Size Results

<table>
<thead>
<tr>
<th>Power and Sample Size</th>
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</table>

2-Sample t Test

Testing mean 1 = mean 2 (versus >)
Calculating power for mean 1 = mean 2 + difference
\( \alpha = 0.05 \) Assumed standard deviation = 7

<table>
<thead>
<tr>
<th>Sample</th>
<th>Difference</th>
<th>Size</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5</td>
<td>20</td>
<td>0.716815</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>40</td>
<td>0.935949</td>
</tr>
</tbody>
</table>

The sample size is for each group.
The output indicates that a design with 20 samples per group (a total of 40) has a ~72% chance of detecting a difference of 5. Generally, this power is considered to be too low. However, a design with 40 samples per group (80 total) achieves a power of ~94%, which is almost always acceptable. Hopefully, the power analysis convinces management to approve the larger sample size.

Assess the Power Curve graph to see how the power varies by the difference. For example, the curve for the sample size of 20 indicates that the smaller design does not achieve 90% power until the difference is approximately 6.5. If increasing the sample size is genuinely cost prohibitive, perhaps accepting 90% power for a difference of 6.5, rather than 5, is acceptable. Use your process knowledge to make this type of determination.

Conclusion

Throughout this column, we’ve been looking at continuous data, and using the 2-sample t-test specifically. For continuous data, you can also use power and sample size analyses to assess ANOVA and DOE designs. However, there are hypothesis tests, and corresponding PSS analyses, for other types of data, such as proportions tests (binomial data) and rates of occurrence (Poisson data).

In general, when you move away from continuous data to these other types of data, your sample size requirements increase. And, there are unique intricacies in each. For instance, in a proportions test, you need a relatively larger sample size to detect a particular difference when your proportion is closer to 0 or 1 than if it is in the middle (0.5). There are many factors that can affect the optimal sample size, but PSS analyses help you navigate these concerns.

After reading this column, I hope you see how PSS analyses combine statistical analyses, processes knowledge, and your requirements to help you derive the optimal sample size for your specific needs. If you don't perform a PSS analysis, you risk performing a study that is either likely to miss an important effect or have an exorbitantly large sample size. Finally, experimentation is an iterative process. As you conduct more studies in an area, you'll develop better estimates to input into PSS analyses and gain a clearer picture of how to proceed.
Standards are intended to guide practitioners to operate in a sound and consistent fashion. It is rare to hear of situations where practitioners have intentionally deviated from standard procedures in violation of a contractual agreement. Expanding the scope of standards from the formal statistical realm to consider standards of professional conduct and behavior offers a multitude of standards-violation situations with severe consequences. These consequences range from professional embarrassment, to academic dismissal and funding prohibitions and finally, to the extreme of criminal prosecution. In response to such scandals, NSF and NIH have pushed universities receiving their funding support to conduct training seminars for graduate students to minimize future research malfeasance. In the fall of 2011, I developed a seminar, “Data Management: Perils of Data Fabrication, Falsification and Confidentiality Breaches” which I have continued to deliver three or four times per semester ever since. This column will describe some of the key features of this seminar that I hope are of interest to ASQ Statistics Division members.

As a preamble, I should note that this seminar is mandatory in that in order to be officially accepted into Ph.D. candidacy, students must attend this seminar and several others. I discovered this requirement upon the first delivery of my seminar (OMG!). Hence, I have been forced to exert considerable effort in the seminar presentation so as to capture the students’ attention and divert their attention from their cell phones. I start the seminar by conducting a brief written survey to determine the group’s awareness of any data fabrication or falsification situations at UCF or elsewhere. Typically, one or two students may be aware of some plagiarism stories but the majority of attendees are not aware of any cases whatsoever.

My opening salvo to catch their attention starts with me describing a “Cliff’s Notes” summary plot of an unnamed book. Let me describe it here and see if you recognize the novel:

A main character (MC) leaves his home country by ship, which is carrying some zoo animals. The ship sinks and the MC ends up in a lifeboat. Aside from some provisions there also happens to be a wild cat sharing the lifeboat! Although the MC tries to feed the cat via fishing, there is ultimately an altercation, in which the MC is knocked unconscious. MC wakes up on shore and asks the folks who greet him about the wild cat. His rescuers think he is delirious from sun exposure.

Have you read or heard of such a book? Several of the students start nodding their heads during my oral description and are eager to share their awareness of Yann Martel’s book, Life of Pi, that was awarded the £50,000 Man Booker Prize in 2002. Whether you have read the book or seen the movie, the summary given above is a virtual match to Life of Pi. Now for the surprising reveal: the plot summary given above is actually taken from the Brazilian author Moacyr Scliar’s book, Max and the Cats, published in 1981 (OMG2)! Martel has admitted that he knew of Scliar’s book through a review written by John Updike in some New York magazine or paper (Martel could not produce the said review indicating that he may have mis-remembered the source!). Eventually, Martel and Scliar had a cordial chat about the situation. Scliar would have preferred to have been made aware in advance about Martel’s plan to use his plot line but graciously commented, “Life of Pi is a very well-written book, that one reads with pleasure. There is no doubt Martel is talented.” So much for a financial settlement!

As an important aside and speaking of financial matters, I happened to capture the following screen shot in the course of securing a copy of Max and the Cats. An obvious side benefit of the seminar (and for the present reader) is the warning to exert extreme caution in using Quick Click!
I’m afraid there is yet more to the Martel affair. In 2016 Martel published another book, *The High Mountains of Portugal*. A key plot line of the book is that the MC deals with grief by walking backwards. In the seminar I mention to the attendees that Martel admitted in an NPR interview (the same one that put me onto his new book) that he got the idea out of his own *imagination*. Having heard this admission I naturally googled, “walking backward grief novel,” that immediately identified the Catherine Austen book, *Walking Backward*, in which a young boy deals with grief by—you guessed it—walking backward. Upon calling this to the attention of Catherine Austen, she responded to me, “. . . that many rip-offs are not consciously done” and she further noted that for regarding conscious rip-offs, “you are so right to growl at those.” If we believe in standards and feel that one is violated, are we not obliged to at least investigate such a transgression?

The next “fun-fact” audience participation segment of the seminar involves the presentation of a list of names and numbers with the teaser, “What do the following names and numbers mean?” Here they are:

<table>
<thead>
<tr>
<th>Name</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fujii</td>
<td>183</td>
</tr>
<tr>
<td>Boldt</td>
<td>96</td>
</tr>
<tr>
<td>Stapel</td>
<td>58</td>
</tr>
<tr>
<td>Maxim</td>
<td>48</td>
</tr>
<tr>
<td>Chen</td>
<td>43</td>
</tr>
<tr>
<td>Zhong</td>
<td>41</td>
</tr>
<tr>
<td>Kato</td>
<td>36</td>
</tr>
<tr>
<td>Hunton</td>
<td>37</td>
</tr>
</tbody>
</table>

Table 1: Names and numbers

What is the story with these numbers? The two usual guesses by attendees are “number of papers published” or “number of citations”. Wrong answers! The reveal is that these are the number of papers that have been *retracted* by these guys! OMG! That is a lot of papers to be even published in the first place. For the seminar, I detail the escapades of Fujii and Stapel. Fujii was a Japanese anesthesiologist who fabricated data on patients never seen and on medicines not administered. Once this modus operandi was discovered, the Japanese Society of Anesthesiologists investigated the
full collection of his 200+ papers which to date has led to the retraction of 183 articles from refereed journals. Evidently, the first wave of his publications following his Ph.D. were legitimate, but once he got into the habit of concocting data for his research, he followed this easier research path until caught.

Stapel, a Dutch psychologist, was another data fabricator who specialized in “collecting” (i.e., making up) data on human behavior in crowds such as the Amsterdam Metro from the friendly confines of his university office. As with Fujii, once it was realized that he was a fabricator, his complete research portfolio was reviewed and paper after paper was retracted. Following his dismissal from his university position, he opted to self-publish an autobiography of how he became an expert data faker (the thrill of tweaking the numbers to achieve just the right level of plausible significance). However, within days of the release of his desperate money-making effort, the plan unraveled as the book became available for free download, which smacks of poetic justice!

I have several other curious examples of fraudulent research that I present in the seminar. Many of these I located thanks to the website retractionwatch.com that monitors research retractions and attempts to get to the rationale of the retractions. I also demo the website ori.hhs.gov that has a tab “Misconduct Case Summaries,” that is effectively a wall of shame, providing the gory details of funded researchers who have been found out and have agreed to severe penalties.

In Part 2 of this column (next Stat Digest issue), I will cover some additional egregious cases of research misconduct and describe more specifically the nature of the transgressions (e.g., tampering with Western Blots). More importantly, I will describe some approaches to discourage research malfeasance. Spoiler alert: develop and implement relevant standards.

FEATuRE

The Dorian Shainin Medal, Recognizing Innovation

Richard D. Shainin

Background

In 2003, ASQ established the Shainin medal to recognize innovation in the development of methods and techniques that improve the quality and reliability of products or services. To date the medal has been awarded 11 times.

Dorian Shainin (1914–2000) was an aeronautical engineer, certified management consultant and innovator. He was a founding member of ASQ and recognized as an honorary member in 1996.

His first statistical innovation was the Hamilton Standard Lot Plot. It used sample data to determine if a lot of incoming material was acceptable or suspect: flagged for 100% inspection. The analysis was graphical and it quickly became a standard for acceptance sampling with variables data. When it was published in 1950, ASQ recognized it with the Brumbaugh Award as the most influential paper of the year.

After his discovery of the Red X® principle in 1947, Dorian’s innovations focused on finding and controlling the Red X®. The Red X® principle recognizes that system variation follows a power function, e.g., Juran’s Pareto principle. That means that no matter how many sources of variation have been discovered and controlled, the remaining variation is dominated by one cause-effect relationship.
The Dorian Shainin Medal, Recognizing Innovation

[often an interaction]. Discovering and controlling that relationship is essential for improving system performance. In complex systems that cause is often hidden. Dorian developed a highly structured and disciplined approach to converge on the identity of the Red X® through a progressive search. He invented 20 unique statistical tools ranging from Component Search through Tolerance Parallelogram to Pre-Control. Dorian had a passion for developing statistical methods that were easy to use and powerful. When analysis was required, it was almost always graphical. He wanted his methods to be accessible to shop floor personnel.

Evaluating Innovation

Innovation is hard work. Ideation (the process of forming ideas) is the recognition of a need and the flash of brilliance that leads to a new approach. Realization is the development work to turn the idea into a usable method. It often requires refinement and multiple iterations to make the technique simple. Da Vinci is reported to have said: “Simplicity is the height of sophistication.” It may be sophisticated but it is not easy. Innovations must be honed and refined to reach that level of sophistication. The final step is utilization. An innovation’s impact can only be judged by the benefits derived from its use.

Consider the development of component search. Dorian was faced with a difficult challenge. His client had high rework costs on an aircraft hydraulic pump with 40 components and was unable to meet the shipping schedule. By this time, Dorian was very familiar with Sir Ronald Fisher’s work in designed experiments. He was also looking at the world through the lens of the Red X® paradigm. He recognized that if he swapped a component between a low output pump and a high output pump, he would be testing the effect of that component as both a main effect or a piece of an interaction. But years of problem solving experience also made him aware that he needed to assess the contribution to variation from the assembly process before he swapped anything. Swapping parts wasn’t a new idea. Aircraft and auto mechanics often swapped out suspect components when trying to repair a plane or car.

Dorian’s innovation was swapping between BOB and WOW units to assess the contributions from the various components and discover interactions. The realization phase involved the formal development of rules for estimating the assembly variation, stage 1, the graphical representation of the elimination phase in stage 2 and the evaluation algorithm for stage 3.

Since its development in 1956, component search has been used thousands of times to identify the assembly process step or the component(s) that contain the Red X®. Seventeen years later, in 1973, Dorian awoke in the middle of the night with an inspiration. He could use the same thought process with a modified algorithm to test the influence of many variables. That was beginning of Variables Search, Shainin’s alternative to fractional factorial experimental designs.

In evaluating submissions for the medal, the Shainin Medal Nominating committee considers uniqueness of the technique (ideation); the degree of development required (realization) and the impact of the new method (utilization). Here are two examples from previous Shainin Medalists:

Patricia Cyr—Shainin Medalist 2014

Harris Corporation designs and manufactures radios for both First-Responder and Military use. Typically, each radio is tested for numerous performance parameters at multiple frequencies in both receive and transmit modes to ensure and document performance and compliance to requirements.

During 2010, Harris was planning to consolidate 600,000 square feet of manufacturing and test equipment to a new facility. The operations team’s challenge was to break everything down, move it, and have everything set up and in production again in 2 weeks. The Quality team’s challenge was to verify that post-move, all test equipment was producing the same results as before the move. The last step was station validation before production could resume. The analysis had to be thorough and quick so as not to delay the resumption of production.
Using univariate statistics was not an option. The sheer number of test parameters across multiple frequencies and power bands tested would have required a small army of engineers several weeks to collect and analyze data. The Type I error associated with such an approach was unacceptable. This challenge had to be overcome to prevent a work stoppage without accepting additional risk using a greatly reduced data set.

Patti Cyr, a statistician with a background in chemical engineering, had experience with multivariate analysis from previous work at Kodak. Multi-variate analysis is most often applied in the pharmaceutical, chemical and biotech industries. Patti recognized the opportunity to apply multivariate methods to a pseudo-spectrum from the radio frequency and functionality data (ideation).

OPLS is normally used to see the influence of multiple inputs on a single output. This electronics adaptation astonished the developer of the original technique. A key feature of the new methodology is the comparison of numerous outputs in a before and after analysis to reveal areas for further investigation. It is a Y to Y analysis as opposed to a more typical X to Y analysis (realization).

The data was collected using an MSA style DOE. Selected units were tested three times each before and after the move. This allowed for consideration of impacts on both average performance and variability because of the move. SIMCA, a software package for multi-variate analysis was used. Although SIMCA uses the correlation matrix for analysis, where each variable has its data centered and scaled to unit variance, additional preprocessing was needed for the data. The responses gathered in the final test have values as small as $10^{-5}$ and as large as $10^8$. It was found that even using the correlation matrix, the responses on the order of $10^8$ overwhelmed the analysis. To handle this difficulty, these responses were first deviated from their target values before the analysis began.

The true advantage using OPLS was in the isolation of the move as the driving force for differences. The use of SIMCA, or other statistical software package, was essential to communicate the findings in terms the engineering community could understand and act upon.

The use of OPLS and preprocessed data allowed for the quick and systematic analysis of over 500 electronic functionality responses, focusing on the tests with the largest shifts in value. The methodology was used by three additional engineers who could successfully assist in the analysis of the data without understanding the intricacies of multivariate analysis.

As desired, and thanks in no small part to this clever application of SIMCA, the team at Harris RF Communications could successfully disconnect, pack, transport, relocate, reinstall, calibrate, and verify that all test equipment was running correctly and producing comparable test results before and after the move within the timeframe required.

This technique is also used extensively at Harris RF to validate changes before they become part of products. Although a change may be made to address a function of the device, OPLS allows for thorough analysis to determine if there are any unintended consequences in other areas of functionality. It is deemed the “control radio process” and is now part of the documented Harris standard procedure for introducing software or hardware changes to existing product lines. Within Harris, it has been applied successfully to dozens of product and process improvements across several product lines, and has allowed changes to be implemented successfully without this risk of unforeseen or undiagnosed performance shifts (utilization).

Ms. Cyr has developed a new methodology comparing the holistic change in system performance following a process or product modification. While the modification is validated there can be unintended effects which might impact the system’s performance characteristics.
This methodology has been applied (utilization) to numerous changes at Harris including:

- Product design changes
- Process design changes
- Test equipment relocation
- Test equipment changes
- Supplier changes such as new supplier or new source lot

The methodology is user friendly allowing quality engineers and managers to identify potential important changes without understanding the underlying statistics.

**Jane Hoying - Shainin Medalist 2008**

In 2003, Jane Hoying, a senior consultant with Shainin was faced with a difficult challenge. An important client had requested the development of a simple and efficient means to solve complex business problems that paralleled the Red X® methodology for solving complex technical problems. Jane was tasked with the assignment. Her management specified a few key parameters: the system had to be true to Dorian’s principles including an investigative approach that converged on hidden root causes based on evidence not expert opinion; it had to be statistically simple and statistically sound; and the analysis and communications needed to be graphical.

Jane brought 25 years of automotive manufacturing experience, a degree in Chemical Engineering and strong success in applying Red X® Problem Solving across a wide range of industries and manufacturing technologies.

Red X® Problem Solving uses strategies based on the physical nature of a manufacturing system or product. It also relies on insights gained in talking to the parts. In a business process, while the system may have some physical elements, the key components are procedural and there are few physical objects to be measured.

Jane had two key insights (ideation). She would have to find a way to talk to the occurrences and she would use a functional description of the system rather than a physical description.

Jane developed a system for talking to the occurrences that revealed which system function had failed. She adopted function models, a simple to understand graphical method for documenting system functional relationships to business processes (realization).

The first application solved a logistics problem that had resisted previous traditional methods such as process sequencing or value stream mapping. By revealing surprising breakdowns in functions, a $1 million annual cost was eliminated and the client had a deeper understanding of how their process was supposed to function.

The TransaXional Methodology has evolved recognizing that there is a hierarchy of functions in every system and that foundational functions must be addressed first.

Within a few years, TransaXional had been applied at six companies on a variety of business process including:

- Logistics
- Production Material Control
- Information Technology
- SAP Implementation
- Quality Systems
- Engineering Systems
- Finance
**FEATURE Continued**

**The Dorian Shainin Medal, Recognizing Innovation**

- Accounting
- Purchasing
- Personnel
- Service Operations Prototype Vehicle Operations
- Manufacturing Operations

The methodology has proven effective in solving business process problems, optimizing business processes and coordinating the implementation of new business systems. Within a few years, it has saved tens of millions of dollars (utilization).

**Summary**

The Shainin Medal has been awarded 11 times to date. Each medalist has been recognized for an innovative method that has improved the quality or reliability of products or services. A nomination form is available on the ASQ website (search for Shainin medal). The submission should communicate ideation, realization and utilization. Testimonials from end users are appreciated. Submissions are due to ASQ by October 1.

**About the Author**

Richard D. Shainin leads the training services team for Shainin—The Red X Company. In this role, he is responsible for the development and delivery of classes and hands-on coaching for Shainin clients worldwide. He is also responsible for Shainin’s third party certification for technical problem solvers and leaders. He has published articles in ASQ’s Quality Engineering, and Six Sigma Forum. His chapter on Multi-vari charts appears in the John Wiley and Sons Encyclopedia of Statistics in Quality and Reliability. His insights on quality, reliability and technical problem solving have been quoted by Bloomberg News, Automotive Engineering, The Detroit Free Press, The Detroit News and Automotive News. He has also been interviewed for radio and television. In 2015, the ASQ Automotive Division named him the Quality Leader of the Year.

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2018 Lean and Six Sigma Conference
26–27 February 2018 | Phoenix, AZ | http://asq.org/

Tips and Tricks: Sustaining Results: This area focuses on implementation, getting results from that implementation, and exploring ways to ensure that the achieved results are sustained.

Lean and Six Sigma in the Age of Digital Transformation: area of focus explores the opportunities that exist to leverage lean and Six Sigma when addressing the challenges and opportunities brought on by disruptive technologies.

Lessons Learned: Implementation of Lean and Six Sigma: In this focus area, we are looking for real-life examples from quality practitioners who have applied lean and Six Sigma tools, methodologies, and techniques.

Masters Series: This focus area explores lean and Six Sigma from the perspective of the seasoned professional and offers advanced context covering the more complex and intricate areas of lean and Six Sigma methodologies.

DATAWorks 2018
20–22 March 2018 | Springfield, VA | https://dataworks2018.org/

DATAWorks is the result of a multi-organization collaboration with the Director of Operational Test & Evaluation within the Office of the Secretary of Defense, NASA, the Institute for Defense Analyses (IDA), and the Section on Statistics in Defense and National Security (SDNS) of the American Statistical Association. This year’s workshop has a new name because we are merging efforts between last year’s Science of Test Workshop (testscience.org) and the Conference on Applied Statistics in Defense (https://casd.wordpress.ncsu.edu/), which evolved from the original Army Conference on Design of Experiments.

The workshop is strategically designed to strengthen the community leveraging rigorous statistical approaches to test design and analysis of data in defense and aerospace. The workshop will have a mix of applied problems, unique methodological approaches, and tutorials from leading academics. The goal is to facilitate collaboration among all involved, including expanding our impact to other government agencies.

2018 World Conference on Quality and Improvement
30 April–2 May 2018 | Seattle, WA | http://asq.org/

There are more than 100 sessions and workshops for you to choose from. Each session will present real-life applications, solutions, and results based on quality principles, while the workshops allow you to dive deeper into quality theories with hands-on learning activities. The “After 5” sessions will even demonstrate how quality can be translated into social activities.

Symposium on Data Science & Statistics
16–19 May 2018 | Reston, VA | http://ww2.amstat.org/

The new annual SDSS combines data science and statistical machine learning with the Interface Foundation of North America’s (IFNA’s) historical strengths in computational statistics, computing science, and data visualization. It stands on the shoulders of giants and will continue the tradition of excellence by providing
an opportunity for researchers and practitioners to share knowledge and establish new collaborations. SDSS is a partnership of the IFNA and ASA. IFNA is responsible for the program, and the ASA is responsible for operations.

**Joint Statistical Meeting 2018**


Topics range from statistical applications to methodology and theory to the expanding boundaries of statistics, such as analytics and data science.

JSM also offers a unique opportunity for statisticians in academia, industry, and government to exchange ideas and explore opportunities for collaboration. Beginning statisticians (including current students) are able to learn from and interact with senior members of the profession.

**RSS 2018 International Conference**


The RSS International Conference has established itself as the only conference in the UK for anyone interested in statistics and data science. Every year, nearly 600 statisticians and data scientists gather from all sectors and from over 30 countries to share information and network, attracted by a varied program of talks and workshops. The 2018 conference will, once again, be organized by ‘streams’ allowing in-depth focus on specialized topics as well as broader presentations on new developments and thinking in statistics.

**62nd Annual Fall Technical Conference**


We invite you to submit abstracts for presentation at the 62nd Annual Fall Technical Conference to be held on October 4–5, 2018 (short courses to be held Oct 3rd), in West Palm Beach, FL. The theme is, “Statistics & Quality: Riding the Big Data Wave.” The Fall Technical Conference has long been a forum for both statistics and quality and is co-sponsored by the American Society for Quality (Chemical and Process Industries Division and Statistics Division) and the American Statistical Association (Section on Physical and Engineering Sciences and Section on Quality and Productivity).
Feb 21, 2018 - John RAMBERG passed away in Tucson, Arizona. Funeral Home Services for John are being provided by Desert Sunset. The obituary was featured in Arizona Daily Star on February 18, 2018.

RAMBERG, John and Joyce

John Ramberg of Tucson passed away peacefully on February 3rd, 2018 after battling Amyotrophic Lateral Sclerosis (ALS). John was a loving husband, caring father/grandfather and an accomplished professor and scholar. Even those who spent time with him in his final days said that he was a teacher until the end. John was born in Stillwater, Minnesota. He received a Bachelor of Electrical Engineering degree from the University of Minnesota in 1961 and marched as part of the band in the Rose Bowl halftime show. Joyce Ramberg of Tucson passed away peacefully on November 27th, 2017 after a courageous battle with cancer. She was a loving wife, mother/grandmother and a dedicated Registered Nurse. Joyce’s living spirit was faithful to her pets and all things outdoors. She was a fighter that moved mountains until her final days. Born in Litchfield, Minnesota, Joyce was the oldest of eight children. She grew up on a farm just east of Grove City and then went on to graduate from the Swedish School of Nursing in Minneapolis. John and Joyce married in 1961 and began their 56 years together in Cincinnati, OH. Driven by John’s pursuit of higher education, they relocated to Ithaca, NY where John attended Cornell University and earned his Master’s. While in New York, John and Joyce welcomed their first two children, Michael and Jill. The family moved to Coralville so that John could take his first teaching position at the University of Iowa in 1967. In 1969, John completed his PhD and daughter, Beth was born. John continued his work at the University while Joyce worked at Mercy Hospital and took up pottery, the first of many art hobbies. Joyce and John loved the outdoors and shared this love with their children. Summers were spent in Minnesota at Joyce’s family farm and John’s family river cabin. They vacationed in Colorado for skiing in the winter and mountain adventures in the summer. In 1978, the family moved to Tucson where John taught and conducted research at the University of Arizona, serving as Head of the Systems and Industrial Engineering Department from 1981 to 1988. He was a fellow of the American Statistical Association (ASA), American Society for Quality (ASQ) and the Institute of Industrial Engineers (IIE). Joyce re-entered the nursing field at Tucson Medical Center as a Scrub Nurse in the operating room. The time in Arizona catalyzed their love for the outdoors. Joyce made numerous long-lasting friends hiking the many canyons and volunteered as a docent at the Arizona Desert Museum. John golfed and could always find a mountain lake to catch fish. They continued the tradition of family vacations to Colorado and took other trips around the world. In 2002, Joyce and John moved to Pagosa Springs, Colorado—hiking, skiing and now living in the state that had always been one of their favorite destinations. During this time, they renewed some long-term friendships and made many new ones. Their last days were spent in Tucson, the town their three children still call “home.” Preceded in death by their parents, Joyce’s sister, Marty and her nephew, Bret as well as the many pets they parented throughout their lives. Survived by Michael (Yvette), Jill (Ed) Bilsky, Beth (Greg) Meisel and grandchildren, Stephen, Nicole, Katie, Jacob, Joshua, Jessica, Charlie and Leo and pets, Keesha and Quincy. Two people, so different but committed to each other. They will be missed dearly. We know that their many colleagues, students, extended family and friends that crossed their paths will miss them as well. In lieu of gifts, donations can be made to a charity dear to your heart. A Celebration of their lives will be held in March. Their ashes will be laid to rest in the Grand Canyon where they enjoyed many adventures together. Arrangements by DESERT SUNSET FUNERAL HOME.

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## Statistics Division Committee Roster 2018

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Good data are often cheaper at almost any price than a costly wrong decision based on wrong information.

W. Edwards Deming