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Discussion of "Bridging the Gap between Theory and Practice in Basic Statistical Process Monitoring"

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Discussion of "Bridging the gap between theory and practice in basic statistical process monitoring"

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General Comments

We congratulate Bill Woodall on his thorough articulation of both the reasons behind the gap between theory and practice and also his recommended solutions for bridging this gap in statistical process monitoring (SPM). We appreciate the opportunity to offer further discussion on these matters. At the outset, we note that the authors of this discussion represent two points along a spectrum with regards to experience in academic research in SPM, with one having conducted research in the area of SPM since the late 1990's and the other a more recent addition to the field of industrial statistics. Despite the disparity in the number of years working in this area, we find ourselves with similar world views on the matters discussed in this (and other) papers regarding the application of industrial statistics.

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Perhaps the similarity of our views on these matters arises from our chosen academic vantage point, in programs with a heavy emphasis on analytics, which provides us with some different application areas than those in schools of engineering or statistics. Despite the industrial origins of most SPM methods, we are inundated with business problems that should be framed as monitoring problems and could draw from the wealth of research in this area. Yet many outside the area of industrial statistics seem unaware that research on SPM exists.

Along with Professor Woodall, we find often find ourselves perplexed by this lack of awareness and believe that closing this gap between theory and practice begins by raising awareness. To raise awareness, we must first identify our target audiences which we have separated into three domains: SPM practitioners, SPM researchers, and "Other" practitioners and researchers. We are hopeful that this is the beginning of a dialogue that can be part of the solution as opposed to the problem.

SPM Practitioners

As stated by Crowder et al. (1997) and quoted by Woodall (2000), "There are few areas of statistical application with a wider gap between methodological development and application than is seen in SPC." Nearly 20 years later, the gap has widened. Although there are a number of reasons for this, one reason, as pointed out in Woodall's article, is the variability in the education and training among practitioners of these methods. In fact, there is no other field of application for statistical methods that we can think of in which the variability in skill level is as great as it is in industrial statistics (which includes SPM). Those who apply SPM may be a shop floor technician with a high-school diploma, a computer network engineer with a bachelor's degree, or a statistician with a Ph.D. This is not a negative, but an overwhelmingly positive testament that highlights the importance of these methods in industry.

Aside from industrial statistics, most statistical methods are applied by researchers in a specific area of study such as natural, physical, medical, or behavioral sciences. And within each of these areas, a "culture" of statistical methodology has emerged, often with distinct differences in paradigms and practice. Within each of these areas, research is conducted to improve the applicability of the statistical methods to these fields. Those who apply statistical methods to their studies must stay abreast of the latest methods in order to maintain the scientific credibility (and publishability) of their work.

However, industrial statistics, and specifically SPM, methods were developed for industry, not for scientific research. Thus, the applications of these methods are not subjected to a lengthy peer review where improvements in the methodology are offered by several independent scientists. The methods were developed to solve specific problems in industry and are meant to be applied by a wide range of practitioners. Most of these practitioners do not have access to the academic journals, and even if they did, we think they would find it difficult to discern "best practices" from the recent research articles related to SPM methodology.

The emergence of industrial statistics and its impact on manufacturing is strangely analogous to what we are seeing with regard to the application of multivariate statistical methods and statistical learning in the information economy. Like SPM methods, data mining methods were developed for applications other than scientific research, and they are widely applied by a variety of people. Armed with a computer and few data skills, individuals can now brand themselves as data scientists. And as with SPM methods, many mass market books and free online resources are being created, while consulting firms are popping up to handle the outsourcing of the analysis. Little of this material is subject to peer review, and we are beginning to see increasingly naïve and misleading applications of the data mining methodologies. We believe that the gap between theory and practice within SPM is going to be quite small compared to the gap between theory and practice in Big Data in the coming years.

Our jobs as academics in the area of applied statistics are to develop useful tools and to educate the workforce on when and how to use them. The practitioner's job is to be an informed user. We believe that practitioners of statistics, including SPM, are becoming more sophisticated over time. This growing tolerance for technical solutions parallels the growth in computing technology, data, recognition of the value of statistical methods, and even the changing focus of education. As mentioned by professor Woodall, we believe that software drives the adoption and practice of statistical methodology. Thus, it is very important for software developers and researchers to work closely to promote sound SPM practice. Researchers who publish a new or enhanced methodology should include the code or macros with their publication in order to encourage adoption of the new methodologies. Software developers should discourage the use of legacy methods that have been proven ineffective or inappropriate through methodological studies. For example, we agree that the range estimator for control charts should be eliminated as the default option in commercial packages.

The National Common Core Standards for primary and secondary education have been adopted by forty-two of the fifty states in the United States. These standards list the ability to compare samples based on center (mean and median) and variability (interquartile range and/or mean absolute deviation) as a required objective of all sixth grade (11-12 year old) students.

And although the standards do not mention the standard deviation explicitly, the use of the normal probability model is an objective of the high school standards, which implies that standard deviation is covered in high school in at least 42 of the 50 states. Thus, the argument that the standard deviation is too difficult is without merit in our current culture, and we agree with Professor Woodall that practitioners can and will apply the right methodology if given the tools and the training.

We believe that with a better foundation in statistical methods, more in-depth training will be increasingly accessible to a broader range of practitioners. Consequently, practitioners will become more informed and the sound application of SPM methods can continue to improve and adapt. To support this, SPM researchers must adapt to the new data and new problems of industry. For example, Megahed and Jones-Farmer (2015) discuss SPM methods related to Big Data applications.

SPM Researchers

Those who hold the "keys to the kingdom" in the academic reward system should review Deming's Fourteen Points, particularly, #8 Drive out fear; #10 Eliminate numerical goals for the workforce; and #14 Eliminate work standards and numerical quotas (Deming, 1982). Fear of not making tenure, numerical goals for the number of articles and level of journal, and numerical quotas for how many papers should be published in order to keep one's job drive bad behavior amongst academics. Bad behavior consists of hasty work that has not been properly justified, incremental work where no real problem is solved, highly mathematical work that is difficult to understand, concealed work where the true value (or lack of value) of a method is hidden, and split work where a single idea is divided into several papers and published in multiple outlets. We should note that these problems are not limited to academics researching in the SPM areas. In fact, these problems are pervasive throughout the academy, and in some areas, perhaps worse than in SPM. However, our focus is on SPM methods.

A search of the Web of Science[1] revealed that in the thirty-five-year span between 1965 and 1999, 900 articles were published that contained a key word or title word "control chart" or "control charts". In the three-year span from 2012-2014, 939 articles were published that contained a key work or title word "control chart" or "control charts". As noted by Professor Woodall, it has become impossible to stay abreast of the literature, even in a narrow domain such as a single type of control chart (e.g. univariate charts for monitoring correlated counts). As academic researchers, we often struggle to reconcile and make sense of the many papers that exist on a single topic. If seasoned researchers cannot figure out the "gold standard" method to apply in a given monitoring scenario, it is not reasonable for us to expect practitioners to do so.

The onus is on the research community to fix this problem. Thus, we want to underscore the eleven suggestions for improving SPM research outlined by Professor Woodall. And to this list, we highlight suggestion #7, that authors should be required by journal editors to discuss practical issues in papers. Specifically, if authors cannot find a real data set to which their method applies, we would infer that practitioners will not be able to either. Thus, papers that introduce or make modifications to methods that are published in applied journals such as *Journal of Quality Technology*, *Quality and Reliability Engineering International*, *Technometrics*, or *Quality Engineering* should have a motivating example, and apply their methods to real or realistic data.

[1] http://www.webofscience.com

We encourage researchers in SPM to consider tackling "grand challenges" in our field. The U.S. Office of Science and Technology defines grand challenges as "ambitious but achievable goals that harness science, technology, and innovation to solve important national or global problems and that have the potential to capture the public's imagination"[2]. The Canadian government has a similar focus on grand challenges in healthcare which they define as "a specific critical barrier that, if removed, would help solve an important health problem in the developing world, with a high likelihood of global impact through widespread implementation"[3]. Solving grand challenges requires persistence, innovation, and leaving one's "comfort zone". Box and Woodall (2012) suggested that "[a]n encouragement for innovation is to put oneself in a position in which, in order to solve a particular scientific problem, one is forced to learn and discover new things."

"Other" Practitioners and Researchers

We define "other" practitioners and researchers as those who are working in fields other than those for which SPM methods have typically been developed. In these fields, practitioners may need to monitor something over time, and researchers may be working to develop these methods. These "other" applications are often related to event detection, such as in public health surveillance, computer network monitoring, social network monitoring, or predictive model deployment. Some "other" applications relate to monitoring for changes in customer or

[2] https://www.whitehouse.gov/administration/eop/ostp/grand-challenges
[3] http://www.grandchallenges.ca/grand-challenges/

employee attitudes or perceptions over time, product reviews, or changes in social media content. In most cases, the problems and challenges in these "other" areas have subtle differences from the traditional applications of SPM methods. For example, in the case of surveillance, it is impossible to stop the process and remove assignable causes.

In a few of these areas, bridges are being built between those who need to monitor and those in the SPM research community. For example, Woodall (2006) introduced the SPM research community to the use of control charts in public health surveillance, and his work catalyzed more research and informed practice in this area. Jones-Farmer et al. (2014) discussed SPM applications to data quality monitoring and Woodall et al. (2016) introduced the SPM research community to the challenges and issues related to social network monitoring. We strongly encourage this type of cross-disciplinary work, which we feel will create opportunities for meaningful research that will increase the applicability and sound practice of SPM methods.

In many cases, "other" researchers have been independently working on similar problems to those encountered in SPM and there is a well-developed literature that seems unaware of the SPM approach. The SPM community may be similarly unaware of the "other" approach. It is not unusual for multiple, sometimes conflicting and sometimes complementary theories or approaches to emerge simultaneously in different (or even the same field). This is true in science, mathematics, government, politics, and many other areas. Ogburn and Thomas (1922) discussed the phenomena of nearly simultaneous, independent inventions including calculus (Newton and Leibnitz), least squares (Legendre and Gauss), and an inexhaustive list of 148 other inventions.

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As an example, beginning in 1999, an area known as Support Vector Data/Domain Description (SVDD) emerged as a retrospective outlier detection methodology in the machine learning literature (see, e.g. Tax and Duin, 1999; Tax and Duin, 2004). The goal of this work was "to make a description of a training set of objects and to detect which new objects resemble this training set" (Tax and Duin, 2004). Although the terminology is different, it is clear that the goal of this work is very similar to the Phase I/Phase II approach in SPM. Sun and Tsung (2003) first recognized the similarities between the SVDD methods and multivariate control charts introducing the kernel density chart (k-chart) based on the SVDD framework. Although a large number of papers about the k-chart have been published since its introduction, there remain many open issues regarding its applicability in practice. Nonetheless, we encourage more work that draws from disciplines other than statistics and engineering. In many cases, work is emerging on SPM-type problems in fields such as machine learning, computational geometry, and data visualization that might help solve some of our own grand challenges. Meanwhile, problems that need SPM methods are arising in many fields such as medicine, marketing, product development, cyber-security, public safety, and others.

Conclusions

Woodall closed his article with a call for us to move our discipline forward, leaving behind criticism and appeals to authority for justification. He highlighted the changes in manufacturing and data collection methods that stretch our existing SPM methodologies and motivate the need for growth. We concur with this recommendation and add that the fabric of our economy has changed so rapidly in the last fifteen years that the very nature of SPM looks nothing like it did in 1931 when Shewhart wrote *Economic Control of the Quality of a Product* (Shewhart, 1931). In fact, in many modern monitoring applications, understanding exactly what process generated the data to be monitored may be impossible. For example, what process is generating product reviews, or network traffic, or social media posts? Thus, just like Woodall suggested changing SPC to SPM, we wonder if we should consider just SM for Statistical Monitoring.

Our eagerness to move the field of SPM (or SM) forward does not imply that we feel that Shewhart and Deming's work is irrelevant. On the contrary, we believe that history is the teacher that builds the foundation for innovation. As Woodall (2017) stated, "there is an incredibly large effort devoted to process monitoring research". We are excited about the future of SPM (or SM) and look forward to the application of these methods in new areas, many of which do not yet exist.

About the Authors

L. Allison Jones-Farmer is the Van Andel chair and professor of Analytics at Miami University. She is also the inaugural Director of the Miami University Center for Analytics and Data Science. She currently serves on the editorial review board for *Journal of Quality*

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Nathaniel T. Stevens is an assistant professor of statistics at the University of San Francisco, in the bachelor of data science and master of analytics programs. He was the 2014 recipient of ASA's Mary G. and Joseph Natrella award and the 2012 recipient of ASQ's Ellis R. Ott award for applied statistics and quality management. He is a member of the ASQ**.**

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