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Statistical Engineering—Forming the Foundations

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INTRODUCTION

Statistical engineering (SE) is a term that has been around in the statistical literature for more than 60 years. Over the years, it has been defined and used by a number of different groups and organizations to encompass a variety of different but sometimes related concepts. Here we focus on the definition proposed by Hoerl and Snee (2010a), which uses the definition of engineering as "the study of how to best utilize scientific and mathematical principles for the benefit of mankind" (p. 52). In other words, this definition considers how existing (and sometimes new) statistical tools can be combined and applied to solve important problems.

We asked a panel of prominent experts, who represent many different areas of academia, research, and industry, to answer a series of questions about the present and future of SE. In this first article we consider:

1. Refinements to the definition of SE
2. What can be learned from other disciplines who have developed engineering subdisciplines
3. Existing examples of successful applications of SE
4. Benefits of developing the field of SE
5. Advantages of developing SE as a formal discipline or subdiscipline

As one of the panelists pointed out, the questions are heavily biased—we, the editors, feel that SE is an idea whose time has come, and we are strongly in favor of the larger statistical community embracing the idea and working together to help take the next steps forward. We readily acknowledge that not all statisticians need to work in the area of SE, but we do feel strongly that as a practicing and researching community, those working in statistics can greatly benefit from having well-defined strategies and demonstrated examples to show how we can be team leaders and team members who solve the large unstructured complex problems facing our organizations. In Part 1 of this panel discussion, we ask questions about the basic definitions of SE and its benefits for statisticians and their workplaces. After the panelists present their thoughts and insights on five questions, the editors highlight some of the key points from the discussion. For those new to SE, these highlights may be a good starting point to give some frame of reference, before returning to the more detailed comments from the panelists.

Definition

Question 1. A new formal definition of statistical engineering has recently been proposed by Hoerl and Snee (2010a) as the study of how to best use known statistical principles and tools to solve high-impact problems for the benefit of mankind. It encompasses the integration of statistical thinking (often at the strategic level) with the application of statistical methods and tools (at the operational level) and has the potential to provide the missing tactical link that will drive proper application of statistical methods based on solid understanding of statistical thinking principles. SE typically involves the appropriate selection and use of multiple statistical tools, integrated with other relevant tools into a comprehensive approach to solving complex problems. Is there anything important that you think is missing from the definition? What do you think are key elements in this definition of SE?

Simpson

First, we owe Roger Hoerl and Ron Snee a hearty thank you and many kudos for developing this idea, which will hopefully gain momentum and become a driving force in government and industry process and product improvement. From my perspective, a major contribution of the SE initiative is to understand the value and importance of planning for, collecting and analyzing data subject to random variation. In order to be effective in embedding statistical thinking and statistical methods in organizations, it will take more than establishing an SE discipline. A culture change is also necessary: Hearts and minds of the statistically illiterate must be transformed.

Hoerl and Snee's definition is an excellent starting point, because it places an emphasis on data driven decision making via the generation and synthesis of multiple analytical tools. Also important in the proposed definition is the reliance on the vertical integration of the decision support system into strategic planning and horizontal exchange from statistical theory to application. So what is missing from the definition? Perhaps the scoping of the tools and methods to statistical based only does not fully capture what is often required in practice. Consider the discipline of response surface methods developed by Box and Wilson in the 1950s. Although the primary emphasis is on the process and product improvement (and often optimization) in the presence of random variation, the tools are a combination of statistical and mathematical. Statistical tools are often most effective in combination with other analytical methods, such as decision analysis. So it might be beneficial to consider the application of statistical and mathematical tools for improving or better understanding systems exposed to random variation.

Several key elements of the SE definition help distinguish it from the practice of statistics. These aspects include highlighting the need to design the analytical solution methodology either via a sequence or combination of existing tools. Hence, the solution methodology is usually multifaceted and tailored to the objective. Probably the most radical change in the way statistics is currently practiced and a key to SE is the requirement to start when the project objectives are defined, not after data are collected. It also requires an interdisciplinary team, where the statistician is on equal footing and interacts with the managers and subject-matter experts.

Vining

Drs. Hoerl and Snee have put a lot of thought into their definition. They have strong motivations for how they have expressed their critical ideas. However, Shainin as well as Steiner and MacKay (2005) have alternative definitions. In all honesty, the final definition is going to evolve over time, perhaps in ways that Drs. Hoerl and Snee would prefer not to see. However, such an evolution would represent more and more people taking ownership of the concept. Such ownership is crucial for SE to have a significant impact on the profession.

No matter how the definition evolves, the key element is "how to best apply statistical theory and methods to solve unstructured, complex problems." This notion goes to the core of how statistical theory and methodology can serve the best interests of humanity.

At this point, I understand the urge for intentional exclusion of certain concepts, such as statistical engineers. Ultimately, the final decision on the definition will evolve over time based on a great deal more discussion from a larger community.

Montgomery

There are two key elements of this definition. The first is that the focus should be on high-impact problems. One of the reasons that Six Sigma (SS) has been successful is the intentional effort to ensure that projects have meaningful business impact, either in terms of cost reduction, expanded sales opportunities, improved customer satisfaction, or other measures that drive business performance or success. The second is that SE must incorporate techniques and methods from other disciplines. Lean Six Sigma (LSS) utilizes many tools from industrial engineering and operations research, particularly those that focus on cycle time reduction, throughput improvement, and elimination of rework and waste. Good SE practice will have to incorporate tools from many other fields depending on the specific problem focus; for example, SE applications in financial services may well utilize many tools from finance, risk analysis, and operations research. Statisticians need to become more broadly educated in some of these fields.

Parker

I believe that Hoerl and Snee (H&S) have proposed a clean, simple definition that includes all of the central tenets of SE. When describing SE to others, I prefer to borrow another H&S phrase that "SE is about engineering statistical sciences to generate better solution approaches" (personal communication).

I agree with H&S that SE aspires to fill the missing link between strategic objectives and operational processes and tools. Though the need to link objectives to the tools seems obvious, from my observation, it is not routinely practiced, or at least not done well. In particular, statisticians too often focus on tools, rather than having the goal to impact the organization. This over-attention to tools can degrade the contribution of statistical sciences. Alternatively, SE seeks to provide the link between the "what" needs to be done at the strategic level and the "how" at the operational level, thereby ensuring cohesiveness and effectiveness in the project execution. A critical function of SE, which is not explicitly stated in the definition, is the active, collaborative role in defining the strategic objectives, namely, defining the right questions. To be effective, we must solve the right problems, and the practice of SE includes being a catalyst to define problems in unequivocal terms as a critical first step. Though this seems obvious, project leadership often lacks the discipline to clearly define the problem so that we can quantitatively detect when we solve it. In some cases, this may be the most important contribution of SE.

SE can benefit by an explicit focus on making decisions: decisions that are defensible, data driven, repeatable, and structured, instead of simply solving problems. To solve high-impact problems, decisions are made to develop, change, or improve a product or process to achieve a high-level organizational objective. The benefactors of these solutions are decision makers. Helping people make decisions in the presence of uncertainty is a simple definition of what a statistician does in practice. SE is consistent with this definition and drives knowledge generation, which empowers better organizational decisions.

A few other minor improvements to the definition could be made. First, I suggest explicitly referring to SE as a discipline, rather than simply "the study of how." Recognition as a discipline is vital to the continued maturation of the ideas contained in SE and furthering the systematic application of SE. Second, the definition seems to unnecessarily imply that the practice of SE is limited to "known statistical principles and tools." I think that SE has a clear role in identifying and promoting research in statistical methods. In fact, SE often requires the research, extension, and adaptation of existing statistical methods. Lastly, though I agree with the strict engineering definition of providing "benefit of mankind," it may not be approachable to many. I suggest that a similar phrase such as for "significant organizational benefits" and/or "benefits to society as a whole" might be helpful.

Clark

Successful implementation of SE will highlight the criteria for improved results. Johnson (2009) reviewed the results of a survey polling nearly 200 SS practitioners to determine the primary reasons why SS projects fail. The two top reasons were the lack of management support and project goals were not linked to finances. Having explicit project objectives and criteria for improved results will help gain management support.

Snee and Hoerl (2007) pointed out that improvement methods need an ultimate objective in order to succeed. For a LSS project, Snee and Hoerl (2007) recommended a holistic approach where the ultimate objective includes both the Lean (reducing waste and cycle time) and SS (reducing variation) viewpoints. The SE methodology used to achieve the ultimate objective of cost-savings would be an integrated approach with respect to the Lean and SS viewpoints.

I propose the following definition for SE. "Statistical engineering is the study of how to best use statistical concepts, methods and tools along with other relevant tools to generate improved results with respect to reducing variation and other system objectives."

Using this definition, Figure 1 illustrates the use of SE in a project. Note the feedback loops between SE methods and operational (subject matter specific) methods and tools. Results generated by the operational methods are evaluated by the SE methods. The evaluation may determine that the project objectives have been achieved or generate new instructions for the operational methods.

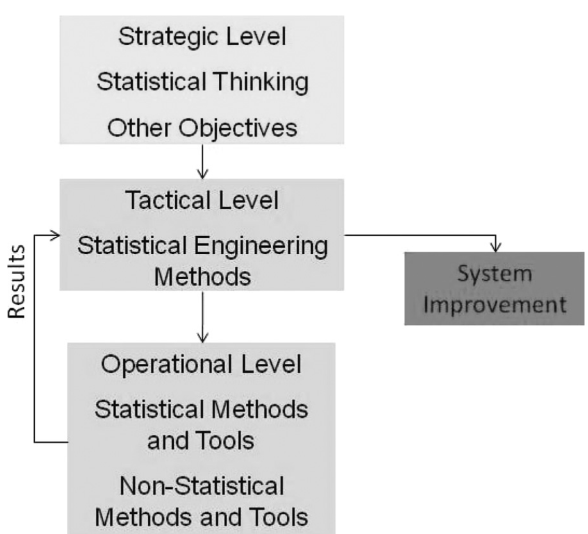

FIGURE 1 Clark's statistical engineering use. (Color figure available online.)

Wilson

For me, the key issue in defining SE is how to distinguish it from applied statistics. Applied statisticians employ statistical thinking, principles, and techniques to the solution of real problems. They may also develop new methodology to help solve these problems. I think that suggesting "Traditionally, applied statistics has referred to the application of individual statistical tools to real problems" (Hoerl and Snee 2010c, p. 69) is a narrow, overly academic interpretation. For example, consider the example of helping an investigator design an experiment, analyze the data, and create appropriate graphical displays to communicate the results; this requires the use of at least three different sets of statistical tools. This suggests that the defining characteristic of SE may be its development of "systems" or "processes" of linked and sequenced tools.

I would not define SE in terms of its "benefit" for "humankind." Clearly there is a desire to position the new field to address "important" problems that have substantive "impact" within organizations. However, SE, like all new fields, will succeed or fail depending on its ability to provide value within the context of its use.

DeHart and Van Mullekom

Although Hoerl and Snee's definition of statistical engineering is appropriate, concise, and mimics other popular definitions of engineering, we believe that some minor revisions could prove useful in the development of this new area. We have found that upon hearing about SE for the first time, many people struggle with the difference between SE and applied statistics. A more descriptive definition may bring clarity to the differences. In a recent article, Hoerl and Snee explain differences between the two by offering a definition of applied statistics (Hoerl and Snee 2011). They discuss similarities and differences and even offer a side-by-side comparison of the dimensions of typical problems. We found this extremely useful and feel that these insights should be incorporated into a refined definition.

The first key element that Hoerl and Snee include in their definition is "known statistical principles and tools." The focus of SE is not on developing new statistical methods but rather on applying known methods to new areas. This leads us to two terms that we feel are missing from the definition: *art* and *translation*. SE is not a pure, precise science with a single correct answer. Instead, SE is an art learned through experience and practice. Statistical engineers creatively apply statistical principles and tools to a variety of problem areas, often beyond the original application area. The ability to use one's theoretical and practical knowledge to translate statistical techniques to new areas clearly differentiates the statistical engineer from the applied statistician.

The other key element that Hoerl and Snee include in their definition is "solving high impact problems for the benefit of mankind." This phrase highlights the fact that statistical engineers should aspire to leadership roles and focus on collaboratively solving complex problems with other scientists and professionals. Given the advances in statistical training and software, statisticians no longer need to be or should be responsible for completing routine analyses. These advances now provide industrial statisticians with the opportunity to focus on larger-scale issues in nontraditional areas. This phrase also emphasizes the practicality of the work of statistical engineers to develop solutions to current, real problems in society.

Even though it is not stated here, several of Hoerl and Snee's articles also mention integrating statistical tools with "information technology (IT) and other sciences." We realized Hoerl and Snee's reasoning for singling out IT when we recently read Kendall and Fulenwider (2000). IT provides a structure for gathering and analyzing data to solve problems as well as a means of communicating results and conclusions. The use of IT to deliver sustainable analytical solutions to large scale problems is critical to enhancing the value of SE. "One-off" models for decision making are not maintainable in the long run. The creation of an IT tool that institutionalizes a developed approach enables better decision making throughout the organization and produces an enduring and sustainable impact.

This leads us to our third term that we feel is missing from the definition: *sustainably solve*. By collaborating with IT, statistical engineers can integrate their solutions into best and standard work practices to sustain the benefits of solutions. Not only will this help to sustain the benefits of solutions, but it can also contribute to a company's bottom line. For example, as Kendall and Fulenwider (2000) pointed out "inefficient data collection leads to increased project and process costs" (p. 34).

In summary, we offer the following refined definition: "SE is the art of translating known statistical principles and tools to sustainably solve high impact problems for the benefit of mankind, often collaboratively with other scientists."

MacKay and Steiner

It is important to note that the term statistical engineering has a long history and has been attributed to Mahalanobis by Corlett (1966). See the Massey University Website http://ifs.massey.ac.nz/research/clusterindividual.php?clustID=14. The Statistical Engineering Division of the National Institute of Standards and Technology (NIST) was founded in 1946. The University of Tennessee in Knoxville hosts an Institute for Statistical Engineering. Morrison (1997) wrote of the role of statistics in engineering, which he calls statistical engineering. Steiner and Mackay (2005) wrote a book with the term in the title. There is considerable variation in the meaning of the term.

We think that it may be a mistake to label the study and application of the tactics as SE. There will be confusion because of the long-term variation in the meaning of the term. Scinto (2011) cited Hoerl and Snee (2010d) and then provided several examples of what he calls SE. These are certainly excellent case studies, but there is little or no discussion of the tactical aspects. One possibility is to add the word *tactical* to SE as in the figures in Hoerl and Snee (2010b).

It is unclear whether the newly proposed definition of SE is limited to quality/process improvement. Hoerl and Snee (2010a) started by describing "urgent problems not being addressed by existing statistically-based approaches to quality improvement" followed by "we propose a different paradigm for the quantitative approaches to quality improvement. We call it statistical engineering" (p. 52). On the other hand, the definition supplied in your question paraphrased from Hoerl and Snee (2010a) is much broader and applies to more than process improvement. In our comments and answers, we will assume that SE applies in a process improvement context. It is within this context that statistical thinking principles are defined and known.

We think it is a mistake to define SE solely as "the study of. . . ." From a marketing perspective (a critical element here), we prefer a less sedentary definition. Our dictionary has four definitions of engineering. The first is active—the application of science for directly useful purposes. Note that in Question 2 below, SE is referred to as *practice*. It should not only be an academic exercise.

We also think it is a mistake to limit SE to "high-impact problems for the benefit of mankind." H&S waver on this point. For example, Hoerl and Snee (2010a) stated, "From an operational perspective, we define SE as the study of how to best utilize statistical concepts, methods and tools and integrate them with information technology and other relevant sciences to generate improved results" (p. 52). And in Hoerl and Snee (2010d), H&S discussed "the best way to apply SE within an organization on a routine basis" (p. 126). We can imagine many valuable applications of SE that are neither high impact nor of obvious benefit to mankind.

Combining these points we suggest the following definition: "Statistical engineering is the application and study of the tactical links between the principles of statistical thinking and known statistical tools. The goal of SE is to ensure the efficient and effective application of statistical methods in process improvement."

Jones

Here is my alternative definition: "Statistical engineering is the practical application of statistical tools and principles to accomplish tasks that benefit society."

These are the problems that I see with the original definition:

1. Mankind is an unintentionally sexist term.
2. Finding the "best" solution is not necessary—an adequate but speedy approach is generally better. Remember the 80–20 rule (80% of the potential benefit of a project can often be accomplished by doing 20% of the work, so getting the last 20% of benefit in exchange for four times the work may not be warranted in every application).
3. Having high impact is desirable but cannot be mandated. In most organizations one needs to do many small things well before one gets the opportunity to make a big contribution. Building the expectation of immediate high impact is potentially counterproductive.
4. Solving problems has a neutral or even positive connotation when applied to math. However, to most people, a problem is a bad thing. Being productive is about accomplishing good things as well as overcoming bad things.

Being able to get things done in spite of difficulties is an important characteristic of a good engineer. Statistical thinking is useful, but there are other important skills to master. The ability to function well inside an organization, by communicating effectively with superiors, colleagues, and people supervised. Effective communication, verbal and written, requires training and lifelong effort.

Any task beyond a certain complexity requires the skills of more than one person. A statistical engineer who is responsible for accomplishing a task needs to be able to identify and coordinate the appropriate human resources towards a common goal. The technical component of such an activity requires that the statistical engineer be acquainted with other technological disciplines.

The nontechnical component requires personal and organizational skills. One useful (but often derided) component of SS training was the inclusion of a number of "soft" tools like quality function deployment (QFD) and failure modes and effects analysis (FMEA). Statistical engineers need to know how to use such tools appropriately and as a sequence of methods, just as they need to know how to design experiments and do a breadth of data analyses.

Question 2. Many other disciplines have subdisciplines involve engineering (computer engineering, marketing engineering, biological engineering, genetic engineering) as a part of their research areas. What can we learn from these areas as we develop the foundations of SE?

DeHart and Van Mullekom

Though we make no claims to have full knowledge of the history of these other disciplines, we do believe that we can learn a great deal from these areas. Auyang (2003) presented an interesting perspective on the origin of chemical engineering that SE may learn from. She discussed how chemical engineering was born out of the need to create a general framework for industrial use. She stated that prior to the development of chemical engineering, industrial chemists were armed with theory but continually had to adapt and reinvent the wheel for each new chemical process which was costly and time consuming. She went on to state that: "In America, chemical engineering was developed by university professors keen on education. Their knowledge was systematically represented for students who could go out to work anywhere. It is a science open to generalization and adaptation" (p. 6).

We feel that this historical view of chemical engineering resonates with modern-day industrial statisticians. Many industrial statisticians are effectively and creatively translating statistical principles and tools to new processes, yet there is no guiding framework or textbook to provide insights and to help accelerate learning for new statisticians. Industrial statisticians and academics need to collaboratively develop the foundations of SE. We must share our knowledge and create a general framework so that future statisticians can leave graduate school with the ability to go out and work anywhere.

Further detailed study of these disciplines may provide even more enlightenment as the foundations of SE are developed. For example, we can learn from DuPont's collaborations with the University of Delaware that led to the development of the university's chemical engineering graduate program in the 1930s. More broadly, we should investigate the motivation of forming other subdisciplines and the resulting benefits. In addition, we should examine how the pioneers in each subdiscipline were able to influence both those on the inside and outside of the movement to embrace and adopt it. How did they identify the key stakeholders in their industries? How did they make people understand that the new term was more than just marketing? Also, how did they communicate and maintain momentum?

Though not an engineering discipline in and of itself, the idea of incorporating successful techniques for encouraging interdisciplinary and transdisciplinary efforts is also an area worth leveraging. Zaman and Goschin (2010) stated, "Another category of scientific cooperation which envisages sustainability refers to transdisciplinarity which usually involves the abolition of borders, barriers between scientific disciplines" (p. 16). Breaking down barriers among economics, engineering, science, and information technology is critical to solving the problems that require SE. Understanding the mindsets, practices, and behaviors that allow for the development of innovative interdisciplinary and transdisciplinary solutions will lessen the growing pains of SE. It will also facilitate the development of cooperative efforts, common language, and knowledge assimilation. Statisticians should think about what role they can take in fostering these interdisciplinary and transdisciplinary relationships.

Simpson

The morphing of business and science disciplines into engineering subdisciplines has been extremely popular over the last 20 years, especially in the last decade. Academia has played a primary role in this process. For example, at Florida State University about 10 years ago, we in the engineering college decided to double the number of engineering disciplines from the traditional five (chemical, civil, electrical, industrial, and mechanical) by adding biochemical, environmental, computer, manufacturing, and aerospace engineering. Business schools are catching on quickly by adding marketing, project, and financial engineering.

The move toward SE should proceed with caution and understand that the purpose is not primarily to attract more students but to dramatically improve businesses, services, and government organizations by unlocking truths about system behavior earlier and more effectively to enable substantial bottom line savings. The recent generation of engineering subdisciplines has a spotty track record of success. Their hurdles are the same facing SE—convincing leadership and executives of the benefits by demonstrating return on investment. The advantage SE has over many subdisciplines is the broad appeal. Aerospace engineering, though it has already demonstrated a return on investment, is primarily limited to the military and commercial aircraft companies. Statistics plays a role in a substantial number of industries whether manufacturing or service, profit or nonprofit.

Montgomery

I can comment on two of these, bioengineering and computer engineering, because we have both academic degree programs at Arizona State University (ASU). Both of these disciplines began as majors within established disciplines. Bioengineering started as a major within the department of chemical and materials engineering, primarily because most of the faculty were already in that department. They collaborated with colleagues in other departments to develop coursework and research programs, and eventually as demand for students with majors in bioengineering and as funding opportunities for the research expanded, a separate academic program and then a department was formed. Computer engineering grew from the department of computer science, which itself started some years earlier as a degree program managed jointly by two departments, industrial engineering and electrical engineering. When student enrollments and employment opportunities grew and funded research programs developed, a new academic department of computer science was formed. Computer engineering remained a minor within that department until recently, when a sufficient critical mass of students and faculty was reached, and a new undergraduate degree in computer engineering was launched.

The key things to note about these disciplines is that they started within established academic programs, they grew a base of students that found employment opportunities, faculty developed research programs that attracted funding from both the private and government sectors, and eventually they evolved into separate academic programs or departments with full accreditation by the Accreditation Board for Engineering and Technology (ABET). I am not certain that we need separate academic departments or even degrees in SE, but the model of developing within established disciplines is a useful one.

Jones

If SE is to become a subdiscipline of statistics, current statistics departments must appreciate the value that such a discipline can bring to the field. An SE program could provide recognized relevance by demonstrating how statistical principles and methods along with other technologies can make a substantial practical difference to society. Statistics departments and industrial engineering departments can collaborate to help this subdiscipline take-off. Industry needs to be another partner in this enterprise. I believe the Institute for Advanced Analytics at North Carolina State is providing a workable model for multidisciplinary academic collaboration combined with partnership with business. The result is students who are ready to enter the work place as quantified by a near 100% placement rate at premium salaries even during an economic downturn.

Hoerl and Snee

First of all, there has to be recognition of SE as a discipline. For example, if chemists did not recognize the discipline of chemical engineering, it would have been difficult for this type of engineering to develop and flourish. So a first step is for the statistics and quality professions to acknowledge that SE is a discipline. Secondly, there need to be good synergistic relationships between science and engineering. Currently, this appears to exist between biostatisticians, biologists, and biochemists working in pharmaceutical development. We need the same mutual respect and cooperation between those focusing on statistical science and those working primarily in SE. Thirdly, there should be journals, conferences, and workshops focused on statistical science and others focused more on SE, as we see with chemistry and chemical engineering.

Parker

Though I have little knowledge on the initial motivation for these other subdisciplines, I suspect that they were borne from an inability or poor efficiency in solving a class of practical problems with existing sciences (e.g., computer, biology, genetics). There was a need to bridge, or engineer, the science and technology to solve these problems. If I am correct, then it seems that the task before us is to make a clear case that existing statistical sciences alone are unable to solve the problems faced by our organizations and/or society as a whole. Once that case is made, then the areas of inadequacy will define the additional expertise required to make SE a distinct discipline.

It seems to me that an obvious question about SE, in which I have seen little discussion, is whether SE should be considered an engineering discipline or a statistical discipline. Hoerl and Snee (2010a) and this venue are clearly focused on the statistical profession versus an engineering venue. Was the formation of computer engineering led by computer scientists or by engineers? Did biologists form the discipline of biological engineering? Answers to these questions may provide us with helpful information and lessons learned as we consider the promotion of SE as a discipline.

Wilson

Consider the definitions provided by the International Council on Systems Engineering (http://www.incose.org/practice/whatissystemseng.aspx).“Systems Engineering is an interdisciplinary approach and means to enable the realization of successful systems.” Systems science, on the other hand, encompasses “The theoretical foundations of systems engineering, including system concepts, systems thinking. . . . [It] provides information about emerging knowledge toward improving the practice of systems engineering, and principles and guidelines for better analysis, . . . development of systems engineering processes, etc. (www.incose.org/practice/techactivities/wg/sseg/)” This delineation seems to parallel the distinction between SE and statistical science.

In defining SE, it will be important to be able to distinguish how statistical science, applied statistics, and SE interact with key building blocks of the discipline. For example, computer science and computer engineering have completely different relationships with computing hardware. Within statistics, how does each of these subdisciplines interact with data? And models?

Vining

In other disciplines, these terms gained traction once funding agencies and academic departments began to embrace them. We are very early in the development of this subdiscipline. I cannot point out any federal funding programs under which SE would fit, even to provide the startup monies. Currently, only a few academics are looking at developing initial courses on SE.

We will not have a true academic subdiscipline until we develop an entire curriculum of courses truly specific to SE. Several of these courses (not just a single course) must be unique to SE. Possible examples are “impact of management systems on SE,” “theory of the proper application of statistical methods to large, unstructured, complex problems,” “theory of defining specific aspects of large unstructured complex problems,” etc. Of course, the expectation is that National Science Foundation (NSF) supports research in such areas as well as course development. Until then I think talk of a serious subdiscipline is premature.

Quality engineering is an example of a still-developing subdiscipline. This journal is now more than 20 years old. Many practitioners carry the title “quality engineer.” However, there are very few academic programs in the field. The American Statistical Society’s (ASQ) Certified Quality Engineer (CQE) examination does provide a concise body of knowledge, and Borror (2008) does elaborate on these concepts. However, I know of no real federal funding programs devoted to this discipline. Even after all these years, quality engineering is not as well-formed a subdiscipline as computer engineering or genetic engineering, which are much younger. Our challenge is to find ways to accelerate this development.

Question 3. Successful applications of “Lean Six Sigma” with the define–measure–analyze–improve–control (DMAIC) structure have been suggested as tangible examples of SE in practice. What are other examples that already exist from which we can leverage learning?

Parker

I think we can leverage much from the discipline of systems engineering, which provides a structured approach for tackling large, complex problems. The *NASA Systems Engineering Handbook* (2007) defines systems engineering as

> . . . a methodological, disciplined approach for the design, realization, technical management, operations, and retirement of a system. A “system” is a construct or collection of different elements that together produce results not obtainable by the elements alone. The

elements, or parts, can include people, hardware, software, facilities, policies, and documents; that is, all things required to produce system-level results. The results include system-level qualities, properties, characteristics, functions, behavior, and performance.

Often, especially within NASA, we think of systems engineering exclusively in the production of a hardware system. The value added by the system as a whole, beyond that contributed independently by the parts, is primarily created by the relationship among the parts; that is, how they are interconnected. In a broader context, I like to think of SE as a systems engineering approach to gain knowledge (rather than build hardware) and explicitly recognize our need to understand the uncertainty in the knowledge obtained and decisions made. Historically, systems engineering was borne from problems too complex to effectively solve with a single engineering discipline. I see clear parallels of this genesis with SE.

MacKay and Steiner

We have developed and used a version of SE (Steiner and MacKay 2005) designed for application in high-volume manufacturing processes. The algorithm grew from a proposal of Shainin (1992). Because of the focused context, the algorithm can be more detailed and prescriptive than DMAIC is. For example, we strongly recommend a sequence of observational studies to isolate the dominant cause of variation before any formal statistical experiments are conducted. Within the algorithm, the tasks required to move through any of the stages are specified.

One of the major challenges is to decide whether "one size fits all" is the correct approach to SE. That is, should SE aim for a process improvement algorithm, like DMAIC, that is designed to be widely applicable or should there be different algorithm for different applications/contexts? We believe that there are major advantages to more focused algorithms, but this is an issue requiring much thought and study. SE must operate within technical and social contexts, and we expect interactions. Indeed, finding better ways to help both individuals and organizations implement existing SE tactics seems to us to be more urgent, difficult, and important than the development of new versions.

Some applications may have additional principles beyond statistical thinking, which will impact the tactics. For example, in the development and improvement of medical treatments, we must adhere to ethical principles. In our version of SE, we start with the assumption that there is a dominant cause of the variation. This assumption has a strong effect on the tactics and tools.

Wilson

One example that could help inform SE is the attempt to integrate statistics into the Department of Defense's (DoD) acquisition test and evaluation process. As new DoD systems are developed, they are put through a series of tests to determine their effectiveness and suitability for purchase and deployment. The National Research Council has issued a series of reports, starting with Cohen et al. (1998), that detail how statistics could lead to substantial improvements in this process. However, to date, only incremental improvements have been achieved, and the overall process does not broadly incorporate statistical thinking or methods. Identifying the technical, institutional, and process roadblocks in changing this process could provide valuable insight for SE.

Clark

Two examples of SE which illustrate useful approaches to process improvement are: the theory of constraints (TOC) and the Hoerl-Snee statistical thinking process improvement strategy.

1. Theory of constraints: Creasey (2009) and Nave (2002) recommended that TOC should be combined with LSS to produce a more effective system improvement methodology. TOC views the system as a set of interdependent links in a chain working toward a common goal. The constraint is the weakest link. In a manufacturing process, the machine station that is the most overloaded might be the weakest link and places a constraint on the throughput of the entire process. In a hospital, nurses of a particular specialty might be a weak link, causing long waiting times. In both cases, one cannot improve throughput without improving the weak link.

The TOC improvement strategy has five steps (see Stein [1997] for details):

- Identify the weak link or constraint.
- Improve or exploit its capability.
- Subordinate other links to the constraint.
- Strengthen the weak link or elevate it.
- Repeat the improvement process. Once the weak link is strengthened, another weak link likely becomes the new constraint.

2. Hoerl-Snee statistical thinking process improvement strategy: Hoerl and Snee (1995) originally formulated a process improvement strategy. See Britz et al. (2000) and Hoerl and Snee (2002) for more details. To begin, one defines the scope and objectives for the improvement effort. Figure 2 displays a flowchart of some portions of the improvement strategy process and lists some example tools to perform the corresponding steps.
3. Two primary features distinguish this strategy from the DMAIC strategy. That is,
   - Improvement occurs in iterative sequential steps. One could call this strategy an enhanced plan–do–check–act (PDCA) approach to improvement.
   - One of the first steps is to remove special-cause sources of variation (see Stauffer 2008). One reason for this is that the problem analysis for removing special causes often differs from the analysis to reduce common-cause variation. Common causes are always present; however, special causes operate in isolated circumstances and often require less effort to remove.

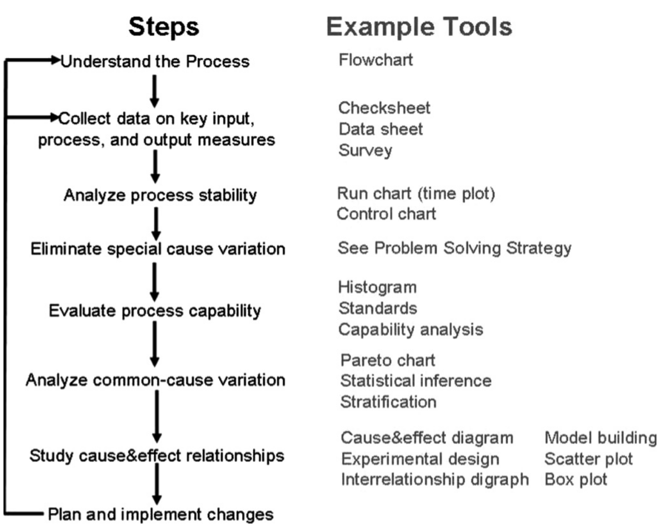

FIGURE 2 **The Hoerl–Snee statistical thinking process improvement strategy. (Color figure available online.)**

DeHart and Van Mullekom

We believe that DuPont statisticians have long been practicing SE. That is, DuPont statisticians have been encouraging the use of statistical thinking and methods throughout the corporation. In fact, Hoerl and Snee referenced two examples from DuPont, product quality management and strategy of experimentation (Hoerl and Snee 2010a). Both systems were built to satisfy a business need and both delivered on solid business results for DuPont. Many more recent examples exist within DuPont. We highlight a few here.

After the recent recession in the United States, everyone is hoping to see into the future and predict the next economic crisis. Statisticians at DuPont are also tackling this issue. DuPont has integrated statistical thinking and methods into their business management. Specifically, they have been involved in forecasting and demand planning to help businesses better prepare for the future. This work has so many of the key elements of SE as defined by Hoerl and Snee (2010a). It is serving a high-level need and has the potential for great financial impact. The problem is very complex and involves a collaborative team. Furthermore, the solution utilizes many tools—statistical, IT, and others.

Many statisticians work in the research and development space at DuPont. They have historically contributed to the development of new product offerings through data analysis and experimental design and recently helped to create a process for product development. Statisticians have worked alongside a team of marketing and technology leaders to develop a corporate stage–gated process for product commercialization. This corporate best practice integrates statistical tools with SS define–measure–analyze–design–verify (DMADV) methodology and DuPont's processes for integrated business management, marketing, and production. The product commercialization process provides DuPont businesses with a framework as they strive to deliver market-driven innovation to their customers.

Standards development and regulatory approvals are key work streams for many members of DuPont's Applied Statistics group. Statisticians frequently interact with organizations such as the American Society for Testing and Materials (ASTM), U.S. Environmental

Protection Agency (EPA), International Safety Equipment Association (ISEA), U.S. Food and Drug Administration (FDA), and many others. This work often requires the combination of many statistical techniques to create a solution that can be applied repeatedly to enable decisions such as cut protection classification and microbial barrier protection determination. In several cases, IT tools including worksheets and macros have been created to enable these analyses.

Simpson

Certainly SS can be a primary means for showcasing SE, because projects are tied to bottom line impacts. The systematic approach to problem solving captured by DMAIC is nothing new though. The scientific methods have been invoked for over 4,000 years, with refinements by notables such as Aristotle, Roger Bacon, and Galileo and obviously greatly enhanced with statistical methods by Ronald Fisher. SE requires a problem-solving framework to anchor the application of the tools.

As we consider the synthesis of the application of the statistical tools traditionally in industry, we need to look no further than the integration of statistical process control, failure modes and effects analysis, design of experiments, and measurement systems analysis as a process breeding examples of SE in manufacturing. Another general discipline, if well practiced, that provides examples of SE, is exploratory data analysis (proposed by John Tukey). Starting an investigation by allowing the data to generate the hypothesis is often the right approach, and the iteration between deductive and inductive reasoning typically requires a diverse application of statistical tools (see deMast and Kemper 2009).

Hoerl and Snee

Other examples we have encountered include the following:

1. Protocols that have been developed for approval of pharmaceuticals—involving more than a one-shot study would be one example. One example is DuPont's strategy of experimentation methodology, which links and sequences various experimental designs, such as screening designs, characterization designs, and response surface designs, into an overall approach to experimentation (Pfeifer 1988; Snee 2009).
2. Scott Paper Company developed a methodology years ago, unfortunately unpublished, to evaluate and improve measurement systems for paper products. Many of these tests were destructive in nature, making it difficult to apply the traditional evaluation methods designed for nondestructive testing. We believe that this was a good example of SE because it linked several methods in a logical sequence to accomplish the objective of evaluating precision, accuracy, linearity, and stability over time. The methods included gauge R&R studies (reproducibility and repeatability) utilizing components of variance methods and analysis of variance, comparisons with standards—using hypothesis testing, regression, and various types of control charts.

As we have often noted, identifying and solving high-impact problems is not new to some statisticians and quality professionals. Several case studies are reported in this publication (also see Scinto 2011). Others will be reported over time enhancing the SE body of knowledge.

Montgomery

LSS is a very broad example of SE. It has applicability across a range of industries and business situations. It has been successful because it utilizes a specific toolset, has a framework for problem solving that utilizes that toolset (DMAIC), and has a strong focus on business results and project-oriented applications. I think that there are other examples of good SE practice. Many aspects of reliability engineering qualify, because engineering design principles and statistical technology must interact to improve product reliability, availability, and maintainability. So do many aspects of designed experiments. Many companies have widespread efforts to ensure that properly designed experiments are utilized throughout their engineering organizations. These efforts are often not related to SS programs within the company, and in many cases these companies do not have formal SS efforts. However, they recognize that designed experiments are critical in many ways to their organizational success, so they devote considerable effort to ensure that the methodology is assimilated into their engineering and business practices. Supply chain management is another example. Effective supply chain management incorporates elements of statistical forecasting, inventory management, logistics, quality engineering, modeling and simulation, and optimization. Principles of statistics, operations research, and business management interact to develop and operate a key business system in many organizations. Some industrial engineering and business schools have extensive supply chain management academic programs.

Jones

I agree that the SS movement has provided many powerful examples of SE. However, SE has the potential to have broader application and increased longevity. SS is hampered by its apparent failure in application to research and development projects. Its original core principles and techniques have been diluted by consulting organizations that provide SS training in a drastically reduced time format. There is no impetus to make SS an academic discipline.

By contrast, with concerted effort, SE could become an academic program with degree requirements and a core curriculum. This would provide more credibility and also increase the likelihood that students of SE would actually be equipped to have success in a business environment.

DMAIC is similar to a scientific method. In principle, there is no reason for SS projects that involve R&D to fail. But tasks in R&D tend to have a more complex technical component. Highly trained scientists and engineers have little patience with what they see as a rote application of simple statistical tools. So, a person attempting to apply statistical thinking and statistical methods in such environments must have a deep understanding of the methods they are promoting as well as some fluency in the technical area of application.

There are many examples, both historical and current, of successful SE applied to research and development. The DuPont Applied Statistics Group under Donald Marquardt had many notable successes from the mid-1970s through the 1980s. There were several successful statistical groups at Bell Laboratories. The creation of the statistical software, S, that has morphed into R came from one of these groups. First under Gerry Hahn and lately under Roger Hoerl, the Applied *Statistics* group at GE Corporate Research and Development has provided a model for SE in R&D. Currently, the more than 100 statisticians at Google are making a huge difference by helping make the knowledge embedded in the Internet accessible to everyone.

My own role is in the development of software to support the design of experiments and data analysis. Modern statistical practice is impossible without software. Generally the team assigned to a high-impact task does not have time to develop software to accomplish their goals. Rather, they cobble together tools that are "good enough" for their current purpose. Software firms that work in direct support of their customers' business goals are doing SE. One specific example of this is a project where a "cobbled together" solution was taking so much computing time that discouraged any further exploration of the problem. A focused solution reduced the computation from days to minutes and allowed the customer to make a series of data-driven decisions with an ultimate value by their accounting of over a billion dollars.

Vining

Personally, I do not see either LSS or DMAIC as examples of SE. LSS is a strategic management approach as a part of an organization's search for corporate excellence. Such a management approach should foster and nurture SE, which is different from being an example of SE. DMAIC is a structured problem-solving approach completely independent of SE. One can apply DMAIC and do no SE. On the other hand, the specific phases of the DMAIC process do provide opportunities for the development and application of SE.

The true SE examples are more on the case study level illustrating how to apply various statistical methods to solve real problems. As a result, the most realistic examples currently available are very specific case studies. We still do not have the theory upon which to base more generic examples. Such an SE theory must extract the common elements to the successful implementations illustrated by the case studies.

Benefits

Question 4. Some of the obvious benefits of developing the field of SE include the following:

a. Produce improved results for complex processes in the workplace
b. Providing leadership roles for statisticians
c. Increasing awareness of statistics as not just a strategy (statistical thinking) or a collection of tools but an integrated approach to problem solving

What other benefits are there to consider?

Hoerl and Snee

First of all, we would like to say that the benefits mentioned above are quite significant in their own right! When statisticians and quality professionals provide leadership, develop solutions to high-impact problems, and develop integrated solutions to problems they will be making significant contributions to their organizations and enhancing their reputations as well as that of the profession.

However, there are more. For one, SE opens up a new frontier for statistical research. The underlying theory of SE is scant at best and needs to be developed. For example, is the DMAIC approach the best we can do for a generic problem-solving methodology? What research indicates that it is or is not? In general, the private sector does not have time to do this research. However, if academia supplied it, there would be significant demand and, we suspect, rapid adoption.

DeHart and Van Mullekom

We would like to expand on the above benefits. For example, SE will not only provide better solutions but also more sustainable solutions. Applying statistical and systems thinking within an interdisciplinary team leads to improved solutions that people believe in. Therefore, the business is more likely to fully implement the solution and sustain it over time.

Another key benefit of developing the field of SE is the idea of leveraging good solutions and strategies. Often, practicing statistical engineers are the inventors of custom solutions for complex problems requiring repeatable data-based solutions. The ability to pick up a case study or textbook and quickly adapt the published solution or strategy to a new problem would dramatically increase efficiency in the fast-paced, challenging economic environment faced by global corporations. Obviously corporate proprietary solutions may create constraints on sharing, but even the ability to leverage within a corporation would be of great benefit. Leveraging solutions can reduce the number of wheel reinventions, speed the time to solve problems, and result in real financial benefits for corporations.

A benefit that may seem antithetical to the ideal of leveraging SE solutions is the development of an intellectual property (IP) suite associated with the application of statistics. Corporations often see processing, product design, materials, chemistry, and biology as areas in which to protect their IP, but statistics and mathematical disciplines are often overlooked. Like most scientists, statisticians lack formal education on the patent process and have very little understanding of the role trade secrets can play in providing a long-lasting competitive advantage. As a result, valuable IP may go unprotected or be lost. The applications of SE involving the novel use of statistics in conjunction with instrumentation or use of a data source can play a key role in the creation, development, and implementation of an IP strategy, which may include patents, trade secrets, and licensing opportunities.

Parker

I wholeheartedly agree with the major benefits clearly articulated in the question above. Providing leadership roles for statisticians will be a clear outcome of successfully practicing SE. Moreover, changing the view of statisticians as relevant, full-team-member collaborators is one of the most significant benefits of practicing SE. There is often a prevailing perception that statisticians are brought into the problem after data collection, and though that might be a role a statistician can play, the most significant impact of statisticians arises from early involvement in the formulation of a solution approach and project planning. We know this to be true; however, to get to the table and be on the team in these embryonic project stages requires a significantly different view of a statistician than the perceived classical role.

Montgomery

I think that (c) above is extremely important. I still have colleagues who think that statistics is something that you do to data after it has been collected. This is less widespread in engineering than it was 10 or 20 years ago, but it is still a problem. If more scientists and engineers recognized and took advantage of the fact that statistical methodology is a vital ingredient to their problem-solving process, everyone would be much better off.

Simpson

Other benefits:

- Increase attractiveness of the career field and increase recruiting and quality of statistical engineers
- More relevant research topics coming from academia—less tool driven, more application and synthesis oriented
- Increased collaboration and relevance with industry
- Not just excellent solutions but laying the foundation for real contribution to the bottom line of any organization—profit oriented or nonprofit
- Opportunities to organize and interpret massive amounts of data collected and tie the information gained to process product understanding and improvement

Vining

The biggest single benefit is being treated as colleagues. Box has said on many occasions, "Why do we aspire to be second-rate mathematicians when we can become first-rate scientists?" SE gives statisticians such an opportunity.

Jones

It is still quite common for most technologists to ignore the presence of variability in systems and processes. This blind spot can lead to mistaken conclusions and wasted resources. One benefit is the accelerated learning that comes from recognition of and allowance for system and process variability in project planning and execution.

Question 5. One of the key ideas proposed by Hoerl and Snee is that SE needs to be a formal discipline with defined structure, theory, and validation. How can we help facilitate this development? And what advantages are there to this approach?

Wilson

Formal disciplines are defined by groups of people with common tools and practices. Disciplines have sets of questions that are recognized as "research worthy"; they have recognized credentials; they have opportunities to share knowledge through journals, conferences, and other outlets for professional work. SE must decide whether it chooses to be a collection of nonacademic practices, with a community of practitioners, or whether it wants to move in the direction of departmental programs, degrees, journals, and professional organizations.

Critically, the formalization of SE will facilitate peer review, as consensus will develop about appropriate methods and practices. Developing SE as a formal discipline also allows the development of a "body of knowledge" that practitioners could be expected to master.

Parker

Recognizing SE as a form discipline has numerous benefits to further promote its maturation and further advance its systematic application. Moreover, SE needs to be seen as a discipline that can be taught to others, repeated on multiple projects, and scalable as an organizational tool, rather than seen as being idiosyncratic. There will certainly be some people who are innately better equipped to perform SE. However, for SE to be recognized as a discipline, it needs to be demonstrated as effective by anyone who has successfully been trained to practice it.

This requires structure, theory, and training methodologies.

Hoerl and Snee

We do not believe that it is possible to have a true discipline without a well-developed theoretical foundation, based on active research in the field. Doing so requires better cooperation between industry, academia, and government. SE will never fully develop as a discipline if it is viewed as something only of interest to business and industry. Professional societies can facilitate the cooperation needed through short courses, conferences, and articles such as this one. The advantage to a cooperative approach is that it would bring the recourses of entire professions to bear on development of SE as a discipline.

DeHart and Van Mullekom

We agree that SE as a formal discipline would prove useful in today's society. Documented case studies and other literature can provide ideas for leveraging SE solutions within and across businesses and industry. But perhaps the key advantage of defined structure, theory, and validation is the development of future statisticians. By teaching these skills in undergraduate and graduate school, statisticians will gain competencies in statistical thinking and translation that allow them to work anywhere and accelerate their ability to make important contributions.

In order to develop the SE discipline, industry and academia must work together. Emerging statisticians will never learn the needed skills if dialogue does not continue to open between industry and academia. Consortiums, seminars, conferences, and partnerships can create the necessary collaborative environment. However, academia must recognize that industrial problems and data do not always meet the assumptions required by statistical theory, nor will businesses have the time to wait for the optimal solution. "Good enough" and "by the deadline" often mean a lot to a company's bottom line. Conversely, industrial statisticians must take time from their busy schedules and share best practices to develop the next generation of statistical talent. In addition, industry must be willing to break down confidentiality barriers, which often make this type of sharing prohibitive.

Vining

A problem here is that we are not dealing with a well-understood, well-structured problem. Once we get an analytics problem well defined and well structured, it becomes very textbook-ish. The trick is recognizing what is the right tool for the job. The success of SE lies in helping people to understand and to recognize the problem's true structure. Once that is understood and the large, complex project is broken into appropriate component parts, the right tools usually follow naturally.

Simpson

SE needs its own identity, universal definition, mission, and vision. Much of the structure, theory, and validation could be adapted from other engineering subdisciplines or even from the well-established fields of industrial engineering and operations research. The similarities between SE and these two fields exist not only in the tools but in the types of problems addressed. In the process of developing the SE discipline, it is imperative that it be sufficiently distinguished from these alternatives.

Leaders in SE can assist the development in the short term in several ways: As the theory evolves along with successful case studies, there needs to be publication outlets. Fortunately, we already have a number of journal possibilities, including *Quality Engineering, Quality and Reliability Engineering International, Journal of Quality Technology*, and *Technometrics*. Over time, a new journal could be formed via collaboration with the professional societies (American Statistical Association [ASA] or ASQ).

Most of the hard work associated with the development of the discipline must take place within the existing cultures of our various industries. Senior statisticians experienced in solving complex problems should share their experience through formal education and find ways to mentor the younger generation. We can also facilitate growth by encouraging and enabling university–industry collaboration for problem solving and development of SE structure and theory. One example is the military test and evaluation community, guided by the Director of

Operational Test and Evaluation. They have initiated university collaboration through a recent research contract with four universities in an effort to mature the SE capabilities within the designed experiments discipline. Much of this effort focuses on supplying practitioners the capability to be successful designing and analyzing large, complex, and unstructured tests. Consider the development of SE theory required to successfully test all of the missions and capabilities of a next-generation fighter or even aircraft carrier. Many of our statistical tools and methods are viable for single entry tests, not necessarily complex systems or systems of systems. Large acquisition programs also require testing across phases of development; so although modification and improvements are made, it is important to leverage the knowledge of past testing to efficiently learn in subsequent phases.

Jones

We need to facilitate and develop a plan to make this happen. I think that establishing a formal discipline will help SE avoid the problems that SS has with the dilution of its core principles and techniques through poor implementations. It may not be possible to immediately instantiate departments of SE. However, a few academic institutions that have notable success early on could make a big difference.

At this stage there is only a broad and rather vague conceptual framework for SE. Whether this idea is successful depends on the quality of thinking and organization applied to the implementation details. There needs to be a critical mass of committed stakeholders.

Montgomery

Good SE involves a toolkit beyond the scope of most statistics department. Collaboration with an engineering department would be fairly easy to initiate. Industrial engineering (IE) departments are the natural collaborators (in some universities business schools can also potentially be valuable partners). Undergraduate industrial engineers have the mathematics background; they take several courses in engineering statistics, quality control, modeling and simulation, deterministic and stochastic operations research, supply chain engineering, and production operations. They get some exposure to regression and design of experiments, although not as much as the undergraduate statistics students. Some IE programs offer SS Green Belt certification to undergraduates that take specific courses and execute their senior design project using the DMAIC approach.

An SE minor or certificate that is jointly administered by statistics and IE and is available to both groups of students seems feasible. A key is to find a set of courses that would work for both parties and to utilize a mixture of required and elective courses that the students would have to take to get the certificate (or minor). Both the statistics and the engineering students should take the senior design course and the teams should be composed of both statistics and engineering students.

At the graduate level, finding a mix of statistics and IE courses that form an SE program within the M.S. framework could be easier. Students from both statistics and IE could pursue separate M.S. degrees within their own departments but still be able to earn the certificate. Certificates at the graduate level in SE could be very popular. At ASU, M.S. students have been able to get a concentration (like a major) in industrial statistics for over 25 years. It has been one of our most popular programs with the IE M.S. degree. We also have a Master of Engineering (M.Eng.) degree with a major in quality and reliability engineering. It is reasonably close to what I think a good SE program should look like. This is an on-line degree and it is very popular. We currently have about 75 students in the program. At ASU our interdisciplinary committee on statistics offers a graduate certificate in statistics. This is one of the most popular graduate certificate programs on campus, attracting students from several disciplines and even non-degree-seeking students. Students pursuing this certificate can also earn a SS Black Belt certification from the Fulton Schools of Engineering. An SE certificate could certainly incorporate a SS certification as well. There are formal academic programs in business analytics emerging. North Carolina State and Northwestern already have programs and at ASU we will start an M.Eng. in business analytics this fall. Graduates of these programs could be very effective at the practice of SE.

EDITORS' DISCUSSION AND CONCLUSIONS

First, we would like to thank all of the panelists for their thoughtful answers to these questions on the basics and benefits of SE. To help the reader synthesize some of the key points made by the panelists, we now provide a short summary of ideas that resonate with us as helpful for understanding and clarification. We have listed the panelist(s) associated with the key ideas within the discussion of each question. For ideas that are interconnected between questions, related comments from other questions are incorporated as well with specific question numbers listed. For questions Q6–11, see the second panel paper (Anderson-Cook et al. 2011). The brevity of our summary precludes including many of the details of the thoughts from being presented, but these are available from the original discussion provided by the panelists.

Question 1

Question 1 solicited suggestions for alterations and additions to the definition of SE. We agree the definition is likely to evolve (Vining) as a broader statistical and nonstatistical community embraces this emerging discipline (Parker, Hoerl & Snee, Q2, Jones, Q9). We see this as healthy and a sign of engagement and key to successful development. Defining SE not just as "the study of" but with explicit mention of application and activity (Steiner & MacKay) matches our sense of participation and involvement. We also agree the inclusion of *tactical* is beneficial (Steiner & MacKay) to highlight the distinction from tools and to connect the "what" of strategic statistical thinking (as defined in Britz et al. 2000) with the operational "how" of statistical tools and methods. SE includes components of strategic statistical thinking (to identify the opportunities within an organization), tactical integration and adaptation of methods to the specific problem, and operational implementation of the specific tools and methodologies to create the required solution.

Shifting from problem solving, with its often negative connotations for management (Jones), to data-driven decision making (Simpson, Parker), understanding uncertainty in knowledge and decisions (Parker, Q3), and delivering improved results (Jones) feels like a more constructive packaging for SE.

Another suggestion which resonates with us is changing the focus of SE from "for the benefit of mankind" to something more actionable and tangible like "benefiting the organization and/or society" (Jones, Wilson, Parker). This change will likely connect well with managers and leaders, who need to deliver results within a bounded institution.

The panelists agree that a cornerstone of SE is the focus on solving large unstructured problems by integrating multiple tools. Several comments encourage broader inclusion of tools beyond those traditionally associated with statistics (Simpson, Clark, Montgomery) and the need to encourage new tool development when needed for particular aspects of a problem (Parker). The synthesizing of tools requires creativity, making it more of an art (DeHart & Van Mullekom), and translation of solutions from one application/area to another (DeHart & Van Mullekom) represents a real opportunity.

The scope of applications for which SE is appropriate is an area where there was some differing opinion and, indeed, Hoerl and Snee (2010a) discussed the application both quite generally and then more restricted to just quality improvement (Steiner & MacKay). Clark proposed the use of SE for system objectives broader than just reducing variation. As applications illustrated in the case studies later in this special issue show, though different methods and approaches are relevant for different situations, the potential for SE is for it to develop and prosper in diverse applications. We would agree that the commonly discussed and more established success stories have before now been mainly in the areas of quality improvement.

The panelists are somewhat divided about the need for SE to focus in high-impact areas. Some feel that this focus would lead to an elevation of the profile of statisticians' work, making their contributions more prominent (Montgomery, Clark, Parker, DeHart & Van Mullekom) and discouraging incremental solutions. Others feel that the successful implementation of SE methods to solve problems throughout an organization (Steiner & MacKay) and provide value within its context of use (Wilson) are valuable contributions. It also seems realistic that the types of applications could not always be mandated (Jones). We think that there is considerable common ground in this area: High-impact projects are most desirable, but valuable contributions can be made across a broad spectrum of problems. We would encourage SE to be applied in both areas: The high-impact problems would be helpful to elevate influence and create more exposure of SE, which can be beneficial for SE development and secure leadership support. On the other hand, the ability to make valuable contributions to a wide range of applications is helpful for gaining broader impact and vitality. For those new to SE, smaller, less prominent projects could serve as a helpful development ground.

Panelists also sought to include a notion of the collaborative, interdisciplinary nature of the effort. Team and interpersonal skills are key ingredients to success (Jones), with statisticians integrated as equal team members (Simpson, DeHart & Van Mullekom) and actively involved starting when the project objectives are defined (Parker, Simpson). These are aspects of the practice of SE that should not be forgotten or minimized.

Several panelists think that some additional clarification about the distinction between the practice of statistics and SE would be helpful (Wilson, Simpson, DeHart & Van Mullekom). We agree that the good practice of statistics rarely involves just a single tool but leans toward an interpretation of the practice of statistics and SE as a continuum, where the complexity and breadth of the solution sought determines where on the spectrum an application may lie. The key ideas that solutions should be multifaceted and tailored to the objectives and evaluated with explicit criteria (Simpson, Clark) and solutions should be sustainably captured using IT (DeHart & Van Mullekom) seem universally applicable to any statistical solution regardless of the complexity of application.

Though any manageable definition is unlikely to be comprehensive enough to include all the aspects of such a rich topic, we propose the following definition as the next step in the ongoing evolution of SE: "Statistical engineering is the collaborative study and application of the tactical links between statistical thinking and statistical and discipline-specific tools with the objective of guiding better understanding of uncertainty in knowledge and decision making to generate improved results to benefit the organization and/or society."

Question 2

Because quite a few science areas have branched out to create engineering subdisciplines or separate disciplines, there is much that we can leverage from their development. Understanding the motivation for forming these new areas and the resulted benefits attained is key to discovering their relevance to influence the growth of SE (DeHart & Van Mullekom). Good models are disciplines where the motivation was for a general framework for industrial use (DeHart & Van Mullekom) or to resolve the inability to solve an important class of practical problems (Parker). Focusing on improving the practice of organizations, unlocking truths, characterizing system behavior, and having a formal strategy to convince leadership of the benefits (Simpson) have been the recipe for success for other new emerging engineering disciplines. Some of the disciplines mentioned as natural examples include biological and computer engineering (Montgomery), systems engineering (Parker, Wilson), and chemical engineering (DeHart & Van Mullekom, Hoerl & Snee).

The development of the foundations of SE requires active collaboration and the establishment of a full partnership between academia and industry (Jones, DeHart & Van Mullekom). Both parties need to encourage interdisciplinary and transdisciplinary efforts (DeHart & Van Mullekom), collaboration between departments (Montgomery, Jones), and funded research programs (Vining, Montgomery). From other disciplines, it is clear that we need to develop specialized university courses (Vining, Montgomery, Jones, Q3) that give formal training on methodologies and skills for solving large, complex problems; defining problems to focus on and metrics to quantify the key aspects of the area; and selecting between available tools.

To gain acceptance and help the area to take off, statisticians need to work on making SE recognized as a discipline (Hoerl & Snee, Parker, Q1, Jones, Q9), with connected but separately defined skills, activities, and required training from statistical science. Achieving synergy between the science (theory and tool development and refinement) and engineering branches of statistics (Hoerl & Snee) will accelerate the growth of both, lead to better training opportunities for students of statistics, and present a unified and broad view of the potential and power of statistics to impact the practice of business and society. Clarification is needed to distinguish statistical science, applied statistics, and SE and formally define how each will interact with some of the core elements of statistics, such as models and data (Wilson).

The panelists raise a number of interesting logistical questions about SE. Some feel that it should be a separate discipline (Hoerl and Snee) with separate academic departments (Jones, Q3), whereas others feel that a subdiscipline without a separate degree program (Montgomery) is more natural. We feel that in the early stages of the evolution of SE, a subdiscipline built within a well-established discipline, might be more productive and efficient and take advantage of some existing resources and foundations. Currently it is not clear that there are sufficient numbers of experts to populate academic ranks and teach these new courses, and students would benefit from exposure to both branches of statistics. Fostering the synergy between the science and engineering parts of statistics are perhaps better served with no formal competition for resources. Another interesting question is whether SE should be treated as a statistical or engineering subdiscipline (Parker, Montgomery, Wilson, Q7). Both groups bring skills and methods to the table, and they work together to create venues where SE takes place. But perhaps at this moment, the statistical community is more motivated to see SE blossom.

Question 3

We are delighted to see the breadth of applications for which the panelists feel SE had already been demonstrated. We agree that so far the focus has been more on case study demonstrations, with a real need to establish the theory and formal methods to make them more broadly accessible and repeatable (Vining, Hoerl & Snee, Q4).

Areas where SE applications have already arisen include: high-volume process manufacturing (Steiner & MacKay, Clark), finance (DeHart & Van Mullekom), pharmaceuticals (Hoerl & Snee), defense (Wilson), new product offering (DeHart & Van Mullekom), measurement systems (Hoerl & Snee), Internet information extraction (Jones), and supply chain management (Montgomery). Within statistics the formal linking of multiple tools is also common in design of experiments (Montgomery, Wilson, Q1), exploratory data analysis (Simpson) and reliability (Montgomery). One important area where demonstrated success would be most welcome is in research and development (Jones).

An interesting question was posed (Steiner & MacKay) about whether one general approach to problems solving (akin to the DMAIC process in Six Sigma) or several specialized and application specific approaches would be more beneficial. More concrete and distinctive details are possible with the specialized approaches but might leave gaps in some classes of problems. We think that one promising path to success could be to focus on the specialized approach in the early stages of SE, with later work planned to connect these methods and find the common elements.

One important common theme is the need for statisticians to develop deep understanding of statistical methods as well as some fluency in the technical areas of specific applications where they were applying SE methods (Jones, Montgomery, Q1).

Question 4

In addition to the obvious benefits (improved results, leadership roles, and increased awareness of statistics) highlighted in the question, the development of SE has the potential to provide substantial impact by contributing to the bottom line (Simpson) and producing more sustainable, fully developed, and implemented solutions (DeHart & Van Mullekom). By fostering a better system view complete with variability, more realistic assumptions can be used to model processes and products, which will lead to opportunities for accelerated learning and improvements (Jones). As more data are collected, organizing and analyzing massive data sets provides the opportunity to tie available information to products and processes to guide understanding and improvement (Simpson).

A formal set of SE approaches will allow for leveraging both across and within businesses, yielding improved speed and quality of results (DeHart & Van Mullekom, Simpson). In addition, solutions from one application will be more readily available to guide practitioners about how to formulate and solve distinct but related problems. Complete SE approaches to analyze and improve processes are potentially patentable, and hence intellectual property valuable to organizations can result (DeHart & Van Mullekom).

New and exciting frontiers of research (Hoerl and Snee) in application and synthesis oriented areas (Simpson) are another benefit, which can drive funding agencies to embrace SE research and help increase healthy and vital collaborations between academia and industry (Simpson).

The role of statistician can evolve to more consistently be a full team member (Vining, Parker) and/or leader (Parker, DeHart & Van Mullekom). Those working in SE can be involved throughout the entire process, from definition of objectives and metrics through implementation of improvements and sustaining the improved results (Montgomery, Parker). This richer job description and higher profile can enhance recruiting of statisticians (Simpson).

Question 5

A formal discipline (or subdiscipline) of SE based on an individual identity, universal definition, mission, and vision (Simpson) should be established based on clearly articulated tools and practices captured in a "body of knowledge" (BOK) with recognized credentials (Wilson). The core of the BOK will be based on a solid theoretical foundation and evolve through active research (Hoerl and Snee). The BOK should include a general framework/structure for breaking large, unstructured problems and processes into components and strategies for identifying the right statistical tools for finding solutions (Vining). These approaches and skills should be repeatable and scalable (Parker). Success should be possible for all those who have been trained in SE (Parker).

Mechanisms for efficiently training future statisticians will accelerate the development of the discipline (DeHart & Van Mullekom) and make it more attractive. It will also help make future statisticians more prepared and competent for challenging jobs and be in a better position to make more valuable contributions to their organizations (DeHart & Van Mullekom). Certificate programs at both the undergraduate and graduate levels for students from diverse academic backgrounds (Montgomery) will help foster broad-based support.

To facilitate the development and dissemination of the research, outlets (journals, dedicated conferences, and conference sessions) to share throughout the peer-reviewed community are needed (Wilson, Hoerl & Snee, Simpson, DeHart & Van Mullekom). In addition to the tactical approaches of combining tools for improving results, we also see a strong need for formal evaluation of matching business needs to the metrics and approaches in the initial phases of problem solving; that is, forming the problems and objectives (Parker, Q1, Simpson, Q1). These outlets will facilitate the development of the BOK of SE and provide opportunities for industry and academia to share their studies and best practices (Wilson, DeHart & Van Mullekom) and also help foster long-term and substantive collaborations between them (Hoerl & Snee, DeHart & Van Mullekom, Simpson). Additional aspects of the collaboration should include industry participation in mentoring and training (Simpson) and mutual sharing of knowledge and forming partnership by actively participating in each other's practices and collaboratively working for the benefits of both parties (DeHart & Van Mullekom).

The success of this evolution of SE as a discipline will be dependent on the effectiveness of the implementation details, and heavy involvement from stakeholders (Jones). Demonstrated performance for improved results based on structure, theory, and training (Parker) are needed and should help garner stakeholder participation and support. A challenge to the fledgling of SE community is to consider whether we are generating a critical mass of support for SE both inside and outside the statistical community (DeHart & Van Mullekom).

The panelists have provided us with considerable food for thought. We, the editors, would like to thank them for their diverse and thoughtful ideas and insights. We hope that you will agree that the core of SE offers many opportunities and great potential benefits for not only the statistical community but also throughout industry, academia, and government.

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