- Collecting data (sampling surveys, design of experiments)
- Quality culture (philosophies of Deming, Juran, etc.)
- Use of quality teams and minute papers for course improvement
- Seven basic tools (including control charts, capability indices and understanding of common and special causes)
- Scientific method (plan–do–check–act)
- Importance of understanding variation and prediction
- More graphical skills
- Communication and people skills
- Working on project from beginning to end
- Case studies of important problems
- Time series (in particular, exponential weighted moving averages)
- Computers and appropriate software
- Basic multivariate analysis
- Messy and large data sets
- Ridge regression, Taguchi methods, response surfaces, nonlinear regression
- Simulation, bootstrapping and so on.
- Cluster analysis, classification.

I believe that this list includes most of the topics Banks wants to teach, at least in a superficial way. As different from Banks, however, I would teach some TQM because I believe that it is important for our students to have some understanding of these principles and the gurus involved in the quality movement. That is, I would like to think that our students would have heard of Deming, Juran, a fishbone, a Pareto chart and benchmarking when they go to industry. Just like they may not be an expert in bootstrapping, they would at least be exposed to some of this terminology associated with TQM.

Banks and I do not differ too much in our views. For example, I also note the consulting activity advocated by Boen and Zahn and their stress on good oral and written communication skills. I think that our problem is introducing this in our programs. In the fall semester, 1993–1994, under a "topics" course number, I plan to give one semester of such a sequence as a trial. I hope that all new applied masters students as well as those interested in our Quality Management programs, will take the course. Not every faculty member, however, agrees with me, and I might be disappointed in the enrollment. I will have more facts in January of 1994 and maybe even by that time have enough students interested in a second semester of such a course, given by a more qualified instructor than Hogg. At least I am following Bob Galvin's advice of "Damn it, do it."

Personal Quality Improvement

After studying all of the ideas from TQM, I am convinced that the only way to improve quality in manufacturing, health and education is to begin with the individuals who are involved. As I left Bob Galvin's office, he reminded me that quality is very personal. People can establish visions, aims and missions for themselves. They can immediately start collecting personal data and discover what "defects" regularly impede them from moving toward their vision. They can then work continually to reduce these personal defects. Once everyone in an organization feels this way, the infrastructure to achieve everything a committed CEO wants has been established.

Even at 68, I am trying to improve every day. So while my trip to organizations practicing continuous process improvement is finished, my own quality journey is far from over.

Comment

Vijayan N. Nair and Daryl Pregibon

Our views and experiences are quite different from those portrayed in David Banks' article. We are much more optimistic about the future of industrial statistics. A broad view of industrial statistics includes applications in science and technology that includes manufacturing, software production, business and marketing and service industries. All these areas share a common need for information, the raw materials of which are data. From the perspective that statistics is the science that transforms data into information, we

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feel that statistics has an important and exciting role to play in industry.

1. RESEARCH

By focusing on quality improvement, this article gives a misleadingly narrow impression of the scope of research in industrial statistics while other areas outlined in the article only scratch the surface of research opportunities.

For example, statistical methods have been an integral part of some recent technological advances in industry. In their *Technometrics* expository article on speech recognition, Juang and Rabiner (1991, p. 251) write: "Speech recognition by machine has come of age in a practical sense.... What makes these practical benefits happen is the recent technological advances that enable speech-recognition systems to respond reliably to nonspecific talkers with a reasonably sized recognition vocabulary. One such major advance is the use of statistical methods, of which hidden Markov modeling is a particularly interesting one." Similar opportunities for statistical methods exist in other high-technology applications involving signature and speaker verification, character and cursive script recognition, image deblurring and robotics. These are just a few examples taken from our own research environment at AT&T. Others can identify equally exciting opportunities in their own environment (e.g., see Sandland, 1993).

Statisticians have, however, been slow in recognizing the role of statistics in many of these areas, and much of the pioneering work has been done by the engineering community. In fact, the lack of involvement by statisticians in real problems has led to wholesale "giveaways" of entire areas of statistical work. Pattern recognition, image analysis and classification methods are a few of the areas where the problems are largely statistical and yet statisticians have been noticeably absent until recently. Fortunately, this is slowly changing as more and more statistical researchers are beginning to appreciate these opportunities and getting involved in real applications.

Even within the area of manufacturing, which seems to be the focus of this article, the research challenges for statisticians are becoming increasingly interesting. Technology is advancing to the state where automated manufacturing is coupled with automated inspection. The response variables with which we are now presented are complex high-dimensional objects such as 35mm color photographs from a vision system. Visual display, graphical analysis and modeling of such data raises many interesting issues. How do we "control chart" such complex objects? How do we compute over them? How do we exploit the spatial aspects of the data in our analysis? Left to their own devices, engineers will massage the original data into a single number summary that they can use with a standard statistical package. This is standard practice even though it results in a considerable loss of useful information. It is ironic that the statistical literature is overflowing with techniques to squeak out an extra percent of (statistical) efficiency when tens of percent disappear before ever seeing these techniques.

Consider the example of integrated circuit (IC) fabrication, where hundreds of ICs are fabricated simultaneously (in a regular array) on a circular silicon disk (a *wafer*) ranging from 5 to 8 in. in diameter. After several months of processing, involving several hundred processing steps, each IC is tested for functionality. These test data contain extremely useful information about the process that is largely ignored by quality control techniques based on overall summary measures such as wafer yield (the proportion of functioning chips on the wafer). If the underlying spatial structure of the test data is exploited as a *wafer map*, defect patterns, such as radial clustering or wipe-outs in a particular quadrant, can often suggest which process steps are likely causes of problems. Yet until recently, very little use has been made of the wafer map data in the IC fabrication industry. Over the last two years, in a collaborative research project with engineers and factory personnel, we have developed statistical and computing methods for analyzing wafer map data to exploit the spatial information for process improvement. This project has presented us with interesting research challenges, ranging from visual displays and graphical analysis of complex wafer map data to methods for monitoring wafer maps for spatial clustering and for automated pattern identification of clustered defects.

To be successful in this kind of research environment, it is important that statisticians are willing to work closely with engineers, and possibly researchers and developers from other disciplines, to fully understand the problem and work toward the solution. Such collaboration is an essential ingredient to successful research in industrial statistics.

While reviewing some of the current areas of research, Professor Banks suggests that research in parameter design (the so-called Taguchi methods) and process control is passé. We disagree with this assertion for several reasons. Even at a purely technical level, there are still many interesting research problems in the area of parameter design such as design and analysis of experiments with dynamic characteristics [see the panel discussion, Nair (1992)]. At a nontechnical level, this assertion is symptomatic of a fundamental problem—where statisticians view themselves as technicians who come "after-the-fact" to "fix" up technical issues and move on to another area. Instead, we should take the view that Taguchi's work has broadened our horizons and has shown how traditional techniques like experimental design can be used in novel ways for variation reduction. The challenge for us is to explore the broad spectrum of engineering ideas and applications to which Taguchi has exposed us and examine the role of statistical methods in these problems more fully.

Similarly, the area of process control presents challenges of its own. For example, several authors (Box and Kramer, 1992; Vander Wiel et al., 1992) have been concerned recently with the important question of how the monitoring techniques in statistical process control can be integrated with the optimization techniques in engineering process control and whether it is possible to develop a conceptual framework to quality improvement that encompasses both approaches. It is true that we have seen an overabundance of papers in process control dealing with yet another control-charting technique. But the challenge is to offer a perspective on where an area should be going, rather than to judge it based on where it has been.

2. PRACTICE

Many theories have been advanced for the competitive success of Japanese industry. Whatever these theories are, it is indisputable that the high quality of Japanese products is a major reason for the gains they have made in international markets. This has been accomplished by, among other things, meticulous attention to and systematic management of their processes. And a key ingredient in their process management is information gathering through extensive collection and analysis of data covering all phases of the product realization process, ranging from market feasibility studies all the way to sales and field support.

During a visit to several high-tech companies in Japan in the mid-1980s, the chief engineer of a new color copying machine told one of us that the use of designed experiments was the singlemost important reason for the high quality of that particular product. Over a three-year product development cycle, they had conducted 48 highly fractional multifactor experiments. And all of these experiments were conducted by the engineers themselves. Highly fractional, multifactor experiments are used extensively in Japanese industry during product and process development (see "Quality practices in Japan" by Box et al., 1988). However, the most commonly used methods even in Japan are simple techniques like the basic seven tools (Box et al., 1988).

It is unclear what message Professor Banks is trying to convey about the use of these simple techniques. Obviously, what is simple depends on an individual's training. Even the notion of displaying data on a scatter plot and looking for patterns can be quite novel to someone on the factory floor not formally trained in quantitative methods. Consider also the fact that, more than forty years after its introduction, the idea of conducting fractional factorial experiments is still quite novel to many Ph.D. level engineers! In our opinion, the important reason for the extensive promotion of simple tools, such as the basic seven, the magnificent seven and QFD, is that they provide a mindset and instill a culture in which decisions are consistently made on a systematic basis using real data and customer input. This may not be profound to someone trained in statistics, but such quantitative thinking is only beginning to take hold in industry.

There has indeed been a tremendous increase in the use of and appreciation for statistical methods in industry over the last decade. Nevertheless, much more needs to be done before the impact is fully realized. Here are just a few of the issues, in no particular order.

- For effective process management, companies should take a coordinated *proactive* approach to data collection, data management and data analysis. With automated measurement systems, it is becoming increasingly easier to collect and store various kinds of data that might be useful to *react* to a perceived processing problem. There should be careful planning and discussion up front on what types of data should be collected, how they are to be analyzed and how the results will be used. Equally important are informed decisions on how the data should be stored in order to avoid the common situation where data on different phases of a process reside in different data bases, each with their own peculiar language for access and retrieval.
- Knowledge that is accumulated about processes and products should be "institutionalized." In Japanese companies, knowledge gained about a process, say by conducting experiments, stays with the company even after the individual has left the job. During discussions in one Japanese company, the engineers brought out notebooks with complete details about experiments that had been run at least ten years earlier. In American companies, on the other hand, such knowledge tends to stay with the individual, leading to tremendous duplication and wasted resources. The problem is particularly acute when the job turnover rate is high. The adoption of ISO9000 standards on documentation and reporting will go some way toward moving US industry to the Japanese model.
- We need to publicize "success stories" on the use of statistics in industry. The use of statistical methods results, in most cases, in steady but not spectacular gains. This contrasts with the marketing hype associated with trendy and often brain-

less "solutions" such as expert systems, fuzzy logic, neural nets and the like. Decision makers in industry will be seduced by such "solutions" unless they hear of success stories involving statistical methods. We have found such anecdotal evidence very effective in convincing them that it is worth allocating the necessary resources. Through publications and talks at conferences, case studies will also serve to attract to the field students who might otherwise pursue careers in engineering.

3. EDUCATION AND TRAINING

There has been considerable discussion in various publications about what courses should be taught to engineers and quality practitioners in industry. A major reason for the ineffectiveness of academic training in industrial statistics is not so much *what* is taught, but *how* it is taught. In this regard, universities in Japan have been even less effective than those in the U.S. In fact, Japanese companies engage in massive (re)training of their employees in statistical methods for quality improvement (see Box et al., 1988).

There are a few things to be learned from the training methods used by Japanese industry. Industrial training in Japan is closely tied with product development and process design organizations, and there is extensive use of case studies directly related to the students' work environment. Courses typically meet several days per month over a period of many months, so students can try out the ideas in job-related projects between class sessions. There is often a follow-up, with the instructor and the student's supervisor, to see how the student has been applying the methods learned in his/her real work environment. In contrast, many training programs in the U.S. are built around the short-course format, with students getting intensive training over a three- to five-day period, with little or no follow-up to consolidate the knowledge gained and to ensure that the methods are being used.

If universities are to respond adequately to the needs of industry in terms of education in industrial statistics, it is imperative that there is a partnership between both groups. Statisticians and others from industry should play an active role, as consultants/advisors, in the development of university curricula in industrial statistics. The faculty members, for their part, should be willing to forge relationships with industrial partners and obtain access to real data and practical experience working on real problems. A fuller appreciation for the context in which statistical methods are used in industry is crucial for developing and teaching courses in industrial statistics. Such experience will also help to shape the research directions.

Comment

T. J. Orchard

David Banks covers a lot of ground, mostly useful and all interesting. Any practicing or potential industrial statistician will benefit from reading and reflecting on the article, even those parts with which they disagree.

It has been a long time since I was in manufacturing industry and I am out of touch with the latest developments in statistical methods. In spite of that I know enough to accept the value of research in the proposed areas. I am now more concerned with management and so I concentrate my remarks on David Banks' thoughts about TQM.

The view seems to be presented that TQM is all very easy and the concepts are just common sense which should be apparent to any high school student. This overlooks the need to sell the contribution that simple tools and statistical thinking can make in process and product improvement. Experts must be aware that what may be common sense to them may not be apparent to less experienced people. (Although my son can now look down to count the rapidly appearing grey hairs on my head, I can still remember his problems in learning to walk. As an expert I knew it was common sense to balance on one foot and move the other, but it was not immediately obvious to him!) If we statisticians are that clever and knowledgeable, we should have the common sense to listen and communicate with our customers in terms they understand. And our customers may be fellow employees needing a bit of advice and training.

In spite of the provocative remarks, I do not doubt David Banks' understanding of what makes a good

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