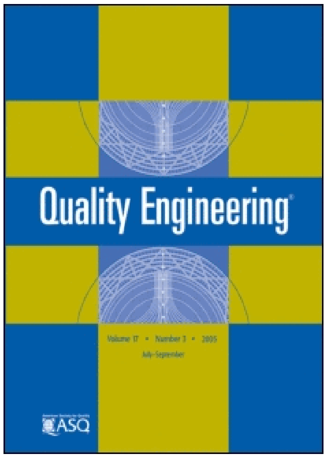

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Rejoinder

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Rejoinder

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We thank all of the participants for their compliments and their useful critiques of our paper and the Shainin System (SS). We also thank the editor and reviewers of this, and earlier versions, who contributed substantially to the paper. Due to space limitations we have addressed only a few of the more contentious issues raised by the discussants.

To frame our response, we make the following three assumptions. First, in order to reduce variation in a specified output, we plan to follow Juran's diagnostic and remedial journeys. That is, we start by identifying one or more causes of the variation (the diagnosis), and then we seek a solution to remove or mediate against the effects of the identified causes (the remedy). Ledolter (JL) notes that this is common to all problem solving systems. Rereading Juran (always a good idea) on the steps in the diagnostic and remedial journeys (see Chapter 5 of Juran & Gryna, 1980), you will see a strong similarity to SS and some of the corresponding tools. Second, we define a cause of variation to be a process input that changes over realizations of the process, such as temperature, component dimensions in an assembly, cavity (in a multicavity moulding process), etc. An input that is fixed, such as a temperature set point or a control procedure, cannot be a cause of the output variation. Third, in the remedial journey, we must change the process to make an improvement. That is, we must change one or more inputs that are normally fixed, such as increase the temperature set point, or add a new error-proofing step to the control procedures.

SHAININ SYSTEM VERSUS SIX SIGMA AND OTHER PROBLEM SOLVING SYSTEMS

We agree with de Mast and Does (MD) and Snee (RS) that all problems cannot be usefully described in terms of excess variation, although Balestracci's (DB) use of Deming's famous quote should remind us that variation reduction is an important component of overall improvement. Should there be a single framework such as DMAIC in six sigma that guides problem solvers through every type of problem as RS proposes? Is there a single description of DMAIC that is universally accepted? Should there be? These questions seem highly debatable and would be of interest to discuss in another paper in this journal. RS points out the strengths of his proposal, but we found his use of the word "elegant" a signal that warns of a dangerous generalization. Novice users especially need more guidance to work through the details of the diagnostic and remedial journeys. Hoerl and Snee (2003), for example, provide two different recipes for problem solving depending on the nature of the cause. We view SS as a competitor to these more prescriptive breakdowns of the diagnostic and remedial journey that can be applied in a

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narrow but important context. We agree with JL's comment "use what seems to fit the problem at hand."

In our view, the SS steps do not replace Six Sigma, but serve as a roadmap through DMAIC for a special class of problems. As RS notes, we did not describe the management system (clearly a key, or more likely the key driver of success) surrounding SS. This omission reflects our ignorance. In the available literature, we found only a brief description of project selection based on the "Rolling Top Five™" and the associated training and certification process (Shainin et al. 1997). For the current version of training and certification, see the Shainin LLC website. As an aside, there you will also find a nice biography of Dorian Shainin.

USE OF DESIGNED EXPERIMENTS

Several discussants criticize Shainin's use (or lack thereof) of experiments. To be clear, we use the word experiment narrowly to describe a study in which process inputs are deliberately changed or controlled. By definition, an experiment is an intervention in the process. In an observational study, we take measurements on the process, possibly both inputs and outputs, without making deliberate changes.

Consider conducting a screening experiment on an existing process early in the diagnostic journey with the goal of identifying large causes of variation, as suggested by RS and Montgomery (DM). The factors in the experiment are process inputs that normally vary—the suspect causes. We must first select these inputs from a large number of possibilities and then decide upon appropriate levels, which is a difficult task if we are unsure of the nature of their variation. To see the effect of an input, we must choose the levels to be moderately extreme relative to its normal range of variation. We must also simultaneously control the levels of these inputs during the experiment (remember these are inputs that normally vary). Randomization is essential because there is a strong possibility of confounding by other inputs uncontrolled during the experiment. Blocking the effects of these other inputs is a challenge, as we may know neither which are important, nor the nature of their variation over time. All of this must take place during normal production. In the end, if we manage to complete the experiment, we will fail to find any large causes we missed in the original factor selection.

Of course, screening experiments can be successful in this context. However, we believe that SS is usually more effective and efficient, that is cheaper, quicker, less likely to collapse, and so on. SS recommends using full factorial experiments (including randomization to protect against confounding), with only a few factors after the list of suspects—that is, possible large causes—has been shortened using elimination and observational studies. In these studies we are likely to learn how the causes vary, which will help in choosing the appropriate levels for the confirmation experiment.

We agree with MD that to solve problems such as their caffeine example (not a variation reduction problem), we must conduct experiments. In variation reduction problems, once we arrive at the remedial journey, if there is not an obvious fix, we need to investigate changes of normally fixed inputs. Here, observational studies are useless and screening designs can be very helpful to sort out the myriad of possibilities. As we pointed out in the remedial journey, not employing the power of screening and other design-based tools, such as response surface methodology and Taguchi desensitization, is a clear weakness of SS.

Finally, we note that following SS prevents confusing the diagnostic and remedial journeys. We have seen many failed experiments that tried to isolate causes and identify the solution at the same time. Such multipurpose experiments are a poor strategy. On this basis, we question the point made by MD at the end of their section 3.2 that hints at such an experiment.

COMMON VERSUS SPECIAL CAUSES

DB and DM take SS to task over the *common* versus *special* cause distinction. We can find no evidence that this distinction is used within SS, or that Shewhart or other control charts are recommended as tools for finding dominant causes. We interpret control charting to mean only ongoing monitoring of the output. We believe that in SS, control charting is replaced by multivari studies and charts where, by collecting and plotting the data carefully, a number of families of causes can be eliminated from consideration. RS notes, as we can also see in some Shainin examples, that we can plot multivari charts for other than time-based families. The Wheeler and Chambers example, (akin to Ott's analysis of means), cited by DB, is just this type of study and, in this example, we think multivari charts using the individual data points are easier to interpret than control charts. In other words, within the method of elimination there is strong direction to collect and plot the data to separate the effects of various time- and location-based families of causes.

Sometimes control charting is not helpful in finding the large causes. Suppose the dominant cause resides in the part-to-part family. That is, we can see almost all of the process variation between consecutive parts. Any control chart based on the output only, regardless of how we plot the data, cannot help identify the causes.

We were puzzled by DM's comment that precontrol will be useless in those situations where an EWMA or CUSUM chart is superior to a Shewhart chart. As we discussed in the paper, precontrol is a simple feedback controller that will provide some benefit when the process exhibits structural variation (Joiner, 1994) that is significant with respect to the specifications. Precontrol is not used in the search for the dominant cause. We do agree with DM that precontrol is a very "ad hoc" controller and there may be superior choices.

THE VALUE OF OPINION

We very much like the comment of Daniel Boorstin: "The greatest obstacle to discovery is not ignorance—it is the illusion of knowledge."

DM and MD provide a discussion of the Shainin claim that "talking to the parts" is far more valuable than constructing a cause and effect diagram in which we get a long list of suspects by brainstorming all possible causes. If we use brainstorming, how should we proceed? One approach is to order the possibilities (using opinion) and test the top choices experimentally. We believe that Shainin's point is that this is less effective than using elimination—what Dao (HD) calls the "Y to X approach." In SS we start with families, not particular causes. Families are defined using process knowledge and statistical considerations. (Can we think of a simple study that might eliminate this family?) Using a method of elimination, we "zoom in" as MD described it, on one or a few final suspects, any or all of which could explain a substantial portion of the variation in the output. These suspects may act separately or as part of an interaction. The effects of these few inputs are then examined experimentally.

The opinions given by process engineers and operators will likely correspond to far fewer possible causes than what we get from a brainstorming session, where the goal is to produce an exhaustive list of possibilities. Using the method of elimination, we may rule out many of the provided opinions, but in the end, we agree with MD that if an opinion is not ruled out by the observational data, it needs to be tested experimentally.

WHAT IF NO DOMINANT CAUSE EXISTS?

The methods and tools in SS are devised based on the assumption that the causes of variation follow a Pareto principle, with a few dominant causes and many others that make small contributions. RS and DM question this assumption and we agree that there may be processes where this assumption does not hold. In this case, SS will fail in its attempt to identify dominant causes.

How will other systems perform in such situations? We issue a challenge to the readers. Follow the link Virtual Manufacturing Process from www.stats.uwaterloo.ca/Faculty/Steiner.shtml. There, you can access a virtual process where you can conduct a wide variety of observational and experimental investigations. There are costs associated with each investigation. Unlike a real problem, we tell you up front that there are five large causes (out of the 60 possibilities), each with roughly the same effect. In combination, the five causes explain about 50% of the output (y300) variation on the standard deviation scale. Your mission is to identify the causes using your favorite problem solving approach. You have a budget of $10,000. In the student version of the process, there are one or two dominant causes as postulated in SS. But the students must find the dominant cause(s) and then implement a remedy within the same budget. Good luck!

It is our belief that in situations with three to six large causes, which RS describes as typical, all data-based methods will struggle if the effects of these causes are roughly equal. However, if the Pareto principle applies, then using SS we may identify the one or two causes that are the largest sources of variation and take remedial action. If we have not met the variation-reduction target, we can start again and identify the next one or two remaining large causes, which will now stand out from the rest. And so on.

In addition, consider the remedial journey when there are a number of equally important causes. Suppose we have already identified a large cause and are able to eliminate its effect completely. Then there will be only a small reduction in the output variation. For instance, in the virtual process example, eliminating the effect of one of the five large causes reduces the output standard deviation by less than 10%. This change in standard deviation would be very difficult to detect. In summary, we believe that when the Pareto principle does not apply, any problem solving system will have trouble achieving substantial variation reduction.

WOW!

We were impressed with HD's claim that he solved "many difficult quality and reliability problems with only one worst of the worst (WOW) part." However, we find it difficult to fit this idea into the overall philosophy of SS. First, to identify a true WOW part we would need to measure a large number of parts. Applying SS, we would, at the very least, compare the WOW to the best of the best (BOB). With only one WOW part there is no basis for comparison and it is not possible to find a dominant cause. Perhaps HD solved the problems using engineering and physical knowledge, but in our view this does not match SS as given in Figure 1 of our original paper.

We do agree with HD that "knowledge and understanding are fostered for the advancement of our problem solving communities" through "the active exchange of ideas." In this spirit, it would be helpful if HD could expand on his discussion of updated SS ideas such as FACTUAL™ (we found the cited article Dao & Maxson, 2007, unhelpful), concept diagram, the problem classification "Event, Feature, Property or Defect," and so on.

CONCLUSION

We wrote this article to highlight what we believe are the strengths and weaknesses of SS. If we have been successful, we hope that problem solvers will take the strengths and incorporate them into their own systems. Those using SS might eliminate some of the weaknesses. Is there anything of value in SS? Could some of the concepts and tools be applied to modern manufacturing processes? DM says no; HD can find no weaknesses. The rest of us fall somewhere between these extreme views. We leave it to the reader to decide.