Discussion: [of 'An overview of the Shainin System™ for quality improvement']

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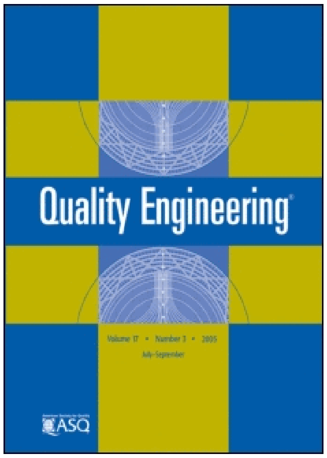

Discussion

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Discussion

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ABSTRACT The article by Steiner, MacKay and Ramberg offers a sound and an accurate description of the Shainin System for quality improvement. Therefore, our comments will not address their representation of the Shainin System, but concern the Shainin System itself.

KEYWORDS discovery, exploratory data analysis, problem solving

HOW GENERIC IS THE SHAININ SYSTEM (SS)?

The type of problems that can be tackled with SS is not clearly demarcated. However, SS has some intrinsic limitations that makes it inappropriate for many problems.

The type of problems that SS copes with can be derived from the principle: "there is a dominant cause of variation in the process output that defines the problem" (p. 4). The type of problems that is tackled is apparently limited to variation problems. A more general form of problems is: a *certain quality characteristic* (*which can be a variable or an event*) *has a probability distribution which does not meet the demands*. This class of problems includes excessive variation, but also process means that are off target, too low yields, too long cycle times, or the occurrence of undesired events. Of course, with some imagination many of these problems could be recast into variation problems, but that is artificial and it is not clear what is gained by it. Moreover, it appears—as we argue below—that the assumption that the problem is a variation problem is quite fundamental in SS.

PROGRESSIVE SEARCH USING FAMILIES OF VARIATION

Finding the dominant cause of a problem is a special case of what is generally called "discovery": the search for possible explanations or solutions (see, e.g., Nickles, 1998). Such a possible explanation or solution is named a *hypothesis* or *conjecture*. Discovery is usually followed up by the *justification* of a hypothesis, which amounts to empirical testing of the hypothesis's implications.

Justification is typically a methodical activity: it follows strict criteria and procedures. For discovery, on the other hand, prescriptions take the form of heuristics, rather than of methods. The idea is that discovery involves a search through spaces of possible solutions. Heuristics are rules that make these searches more efficient.

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De Mast (2003) and De Mast and Bergman (2006) discuss a number of heuristics for discovery that are effective in industrial quality improvement. One of these is a heuristic that is named *Zooming-in strategy*. The idea is to divide the class of potential causes into subclasses and using the nature of the problem to decide in which of these subclasses the dominant cause is to be found, thus eliminating causes that are in the other subclasses. Progressive search as described by the authors is identical to the zooming-in strategy, with families of variation playing the role of subclasses. Other heuristics that are mentioned in De Mast and Bergman (2006) are "thinking in standard categories" (e.g., machine, method, measurement, material, environment), "pattern recognition" and "thinking in analogies."

THE ROLE OF OPINIONS AND CONVICTIONS IN DISCOVERY

For the sake of discovering potential causes one uses—in an informal manner—various sources of information: observations, accepted (technical) knowledge, convictions of persons who work with the process, and so on. In SS, however, the use of convictions and opinions is rejected for the identification of potential causes. Compare, for example, the statement "SS shuns brainstorming and cause-and-effect diagrams when screening possible causes" and the claim that "there is no place for subjective methods as brainstorming or fish bone diagrams in serious problem solving" (p. 6). We want to make some comments about this claim.

Does using Opinions and Convictions Compromise "Objectivity"?

There are several approaches for making inferences (see e.g., Maher, 1998). One of these is the so-called "hypothetico-deductive" method. This method says that it is of no importance how potential causes are found, as long as their effect is empirically verified (by deducing testable consequences from them). An other method is "inductive generalisation" (or "enumerative induction"). In this method potential causes are derived from observations and also justified by these same observations.

SS seems to combine the data-based identification of potential causes of inductive generalisation with the deductive testing of potential causes in a succeeding stage. This testing stage is what ensures "objectivity," not the discovery stage. In other words, since potential causes are experimentally confirmed before they are accepted anyway, we see no reason to declare the use of opinions, or even wild guesses, inadmissable.

Is the use of Observational Data for Discovery more Effective?

SS claims that using inductive reasoning from observations is more effective than using convictions and knowledge of engineers and operators. This claim—which is an empirical claim—should be substantiated with evidence. It means something like: Inductive reasoning from observations succeeds more often in identifying a real cause as a potential cause than using opinions. This seems, however, highly situation dependent. In many processes the engineers have knowledge of many sources of variation and we see no point in refusing to take this knowledge along as hypothesised causes. Moreover, reasoning from observations will help identify only sources of variation that actually vary during usual manufacturing. However, many factors in the process that affect quality and could be used to arrive at improvements are kept constant during normal production, and these will not show up as patterns in observational data.

Rejecting the use of Opinions Limits the Applicability of the Approach

This last points seems to us the crux. If the type of problems for which the approach is used is limited to variation problems (see our point 1.) then clue generation based on data seems more effective than using convictions and opinions. For other types of projects, however, the opposite could prove true. We give one example of such an improvement project.

The objective of a certain improvement project was the reduction of the cycle time of a caffeine extraction process while keeping the resulting caffeine percentage of the coffee safely below a certain limit. This is not a variation problem, and the principle ("there is a dominant cause of variation in the process output that defines the problem") does not hold. The main influence factors in this process (such as the extraction time, the number of extractions and the amount of solvent) were all known to the engineers. Their precise effect onto cycle time and caffeine percentage, however, were not, and the project focussed on experiments to model these effects. Using brainstorming the main influence factors were rapidly discovered. Had we used observational data, however, these influence factors would not have been discovered, because their constant settings during production have as a result that their effect does not show up as variation patterns in observational data.

THE MINOR VALUE ATTACHED TO EXPERIMENTATION IN SS

The authors remark that "However, in comparison to other approaches, in SS, the use of experimentation is subordinated to observational investigations" (p. 12). Again, this position limits the applicability of the approach. There are many improvement projects in which the focus of the project is the identification of the dominant cause of the problem. However, in many projects identification of dominant causes is one thing, but finding out the exact relationship with the quality characteristic under study is a second. Experimentation is the cornerstone for learning about relationships; obervational data are typically less suited for this purpose. The project that was given as an example in our point 3.3 may illustrate this point.

COMMON CAUSES AND SPECIAL CAUSES OF VARIATION

"For variation reduction problems, using families of variation and the method of elimination is a more effective way to partition the causes than is the classical Statistical Process Control (SPC) division into common and special causes" (p. 7).

Divisions of influence factors, causes or types of variation are only sensible in their context. The common causes/special causes distinction was introduced in the context of on-line process monitoring, where a criterion was needed that indicates which variation patterns should be an incentive for action, and which should not. Useful as the division may be in this context, we agree with the authors that the distinction is of limited use in the context of quality improvement projects/SS.

IMPORTANCE OF ESTABLISHING THE MAGNITUDE OF THE PROBLEM

Also in the Six Sigma program a process capability study is performed in the early stages of an improvement project (step 4 of the DMAIC strategy, see e.g., De Mast et al. 2006). In our experience, one of the reasons why this study is so valuable, is that it gives a verification of the problem statement. The translation of a problem into a measurable characteristic, the related measurement procedure, and the posed specifications are in many projects nothing more than intelligent guesses. The process capability study verifies that the problem definition actually manages to capture the felt problem.

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