R&D

SOFTWARE FOR SCIENTISTS

DOE Requires Careful Planning

Here are four common mistakes researchers make when using the design of experiments (DOE) approach.

In industrial product development labs, researchers still commonly develop products using the method of successive approximation. By this method, the experimenter conducts a series of many experiments, each typically involving the testing of only one or two prototypes. In each prototype usually only one component is adjusted.

By contrast, the method of design of experiments (DOE) commonly requires far fewer experiments—usually one or two. However, each experiment requires preparing several prototypes for testing. Moreover, more than one component is usually adjusted in each prototype. This makes the DOE approach more complex and resource-intensive in the short term. The payoff is that DOE ultimately yields far greater gains with less overall work.

It often takes some practical experience with DOE for experimenters to understand the subtlies of the up-front plannning effort needed to assure a successful outcome. Here are four common mistakes that lead to failures in industrial R&D work:

1. Underestimating the background noise inherent in the experiment. Experimenters use different test instruments to measure different product performance and quality characteristics (responses). Each instrument usually has precision limits reported by the manufacturer. The temptation is to assume that these precision limits are equal to the overall uncertainty (background noise) associated with their response measurements. However, these precision limits are only one small component of the overall background noise, which is also called overall experimental error.

By far the larger contributors to background noise are the activities of preparing the prototypes and running the tests. This means that, while re-testing the same prototype may yield good agreement between test values (good instrument precision), test results often disagree substantially when a prototype of a given composition is prepared and tested more than once on separate occasions. The disagreement will be even greater when the prototypes are prepared and tested by different personnel, perhaps using different equipment. This overall background noise sets the baseline for quantifying the variable effects—that is, defining how changes in the study variables change the responses. No experimental work, designed or otherwise, can define these effects with any certainty if the baseline noise is too great.

> **The Four 'Don'ts' of DOE**
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> **1** **Don't underestimate the background noise inherent in the experiment.**
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> **2** **Don't restrict the study variable ranges.**
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> **3** **Don't study too many experiment variables in one experiment.**
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> **4** **Don't use the wrong statistical design type for the variables and / or goals.**

It is vital to first quantify the actual magnitude of the overall background noise and then to reduce it to acceptable limits prior to carrying out the work of a designed experiment.

2. Overly restricting the study variable ranges. In successive approximation experiments the primary goal is incremental product improvement. Each prototype is considered a possible replacement for the current product. Consequently, the experimenter will often restrict the variable range (the difference between the lowest and highest level setting) due to considerations of cost and a guess about the effect the change will have on the system's responses.

However, the goal of DOE is quantitative definition of variable effects. It is not assumed that any of the prototypes prepared as part of the experiment will replace the current product. Rather, the quantitative definition of effects is used to define the optimum product configuration. Therefore, the greater the difference in the variable levels between prototypes, the greater the difference in the test results (the variable effect).

It's important to remember when setting variable ranges that DOE's goal is knowledge about the variable effects, not just incremental product improvement.

3. Studying too many experiment variables in one experiment. DOE has two elements that handle the added complexity of studying more than one variable at a time. The first is the experiment design matrix, which concisely defines the number of prototypes, the exact composition of each, and the specific order of their preparation. The second element is the analysis of the test results. A correctly executed analysis of a designed experiment can eliminate the arbitrary interpretation of the results and the corresponding false conclusions about what is or is not important and the best way to make the product better.

However, including too many variables in one experiment makes it difficult to generate a design containing a manageable number of required prototypes. It also adds substantial complexity to the numerical analysis of the test results. Even with DOE, it is advisable to restrict your studies to at most five variables in any one experiment.

4. Using the wrong statistical design type for the variables and/or goals. The Plackett-Burman design is an example of an often misused statistical experiment design type. Plackett-Burman designs are "screening" designs that experimenters use to study several variables in one experiment. These small designs may require the experimenter to prepare as few as one more prototype than the number of study variables (e.g., seven prototypes for six variables). But the experimenter pays a price for the "efficiency" of Plackett-Burman designs.

The price is this—the effects of interactions between study variables on the measured responses are superimposed on the direct (main) effects of the study variables. The data analysis cannot decouple these effects to determine how much can be attributed to the study variable and how much may be actually due to the superimposed interaction. This means that Plackett-Burman designs should be used only to find out which variables and variable interactions do not affect the responses and can be eliminated from further consideration. However, when experimenters use Plackett-Burman designs to study variable effects, they often attribute the coupled effects to the variables, and use the information to make decisions on how to change the product.

The impact of these four common causes of R&D failures can be minimized by careful up-front planning.

—Richard Verseput

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