# DOE Breaks Traditional R&D Mold

**Design-of-Experiments practices depart from the linear way of performing R&D by helping users examine multiple variables.**

Everyday life, for the most part, is a series of one-dimensional experiences. We generally have a linear sense of the progression of time—we do one thing at a time. It is even argued that we can only keep one thought at a time in our head.

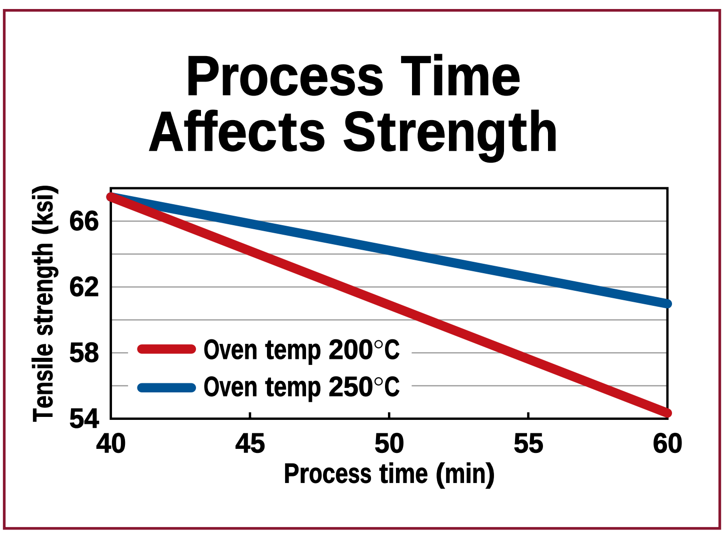
Thus our approach to science and engineering has always been to study one thing at a time. Called successive approximation or, more correctly, trial and error, until now these one-thing-at-a-time approaches were standard practice. However, a portal is now open that all scientists and engineers will ultimately pass through. On the familiar side of the portal is the traditional world of one-dimensional science and engineering. On the other side is n-dimensional R&D.

N-dimensional R&D is the practice of studying more than one thing at a time. It is thus a multivariate approach, and its core methodology is design of experiments (DOE). N-dimensional R&D is the way science and engineering will be done from now on. Why? Quite simply because no one will let you do it any other way. Who might stop you? Everyone might: your bosses, your sponsors, your funding agencies, and, most of all, your competitors.

Industry is all too aware that the global "village" is a fiercely competitive war zone. Industry simply cannot afford to do one-thing-at-a-time R&D anymore. This is why DOE-based multivariate studies are becoming common in most leading-edge companies.

Academia is also coming on board, including DOE in many core science curricula. Even 10 years ago DOE approaches were rarely taught. Today DOE methods are becoming part of the normal coursework at many colleges and universities. This means that the next generation of science and engineering professionals, already competent with computers, will also be competent with DOE.

There is another important driver for n-dimensional R&D—interaction effects. In many systems the materials interact with each other and with the manufacturing processes. Often these interaction effects are the principal drivers of product quality and performance. By definition, two components A and B interact if the observed effect of changing component A on a given response is different at different settings of component B. In other words, the effect of changing component A depends on the specific level setting of component B.




**Studying just time and temperature components in an experiment results in a four-dimensional analysis.**

The above figure illustrates an interaction effect between two process components—process time and oven temperature—on the tensile strength of a product. As the figure shows, product tensile strength decreases as process time increases. However, the decrease is much more dramatic when the oven temperature is reduced from 250°C to 200°C. Thus, the relative strength of the process time effect depends on the oven temperature.

Unless you study more than one thing at a time, experimental data will contain no information about interaction effects, such as whether or not the effects exist, and if so, how important they really are. The more important they are, the more the knowledge gap limits your ability to design robust products that are truly optimized.

However, if studying two or more

components in the same experiment sounds simple—think again. Once you decide to study two or more system components in the same experiment (a multivariate study), you enter a realm of geometrically increasing complexity. The "n" in n-dimensional is geometric. A simple example: say you want to study the effects of changing both process time and oven temperature in the same experiment. That is only two components, so n = 2, right? Not exactly. That's because we must add a dimension for the interaction between time and temperature.

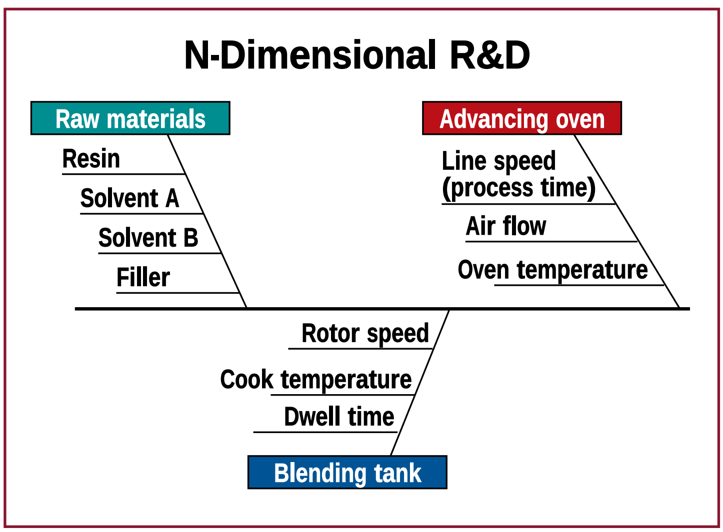
It turns out that to really make sense of the data from multivariate studies, you have to employ numerical analysis, so add one more dimension for that. Let me explain: given only one study variable designated *x*, to obtain a straight line equation of the form $y = mx + b$, we must estimate the coefficient m, the first dimension, and the constant b, the second dimension. The constant b is the "numerical analysis" dimension.

So, tallying up, we have one dimension each for time and temperature, one dimension for the interaction, and one for numerical analysis—we're already up to four dimensions! In fact, we really need even more dimensions so we can (1) accurately estimate the background noise—also called experimental error; (2) address curvilinear and nonlinear effects; and (3) break the dependency of the data analysis results on the experiment design.

Each of these dimensions translates into one or more prototype samples (or runs) that you need to prepare and test as part of a well-designed experiment. Fortunately, good DOE software will automatically determine the correct number of dimensions (n) for any given number of study components. It will then generate an experiment design that defines both the number and composition of the prototype samples for the study.

Once you begin a DOE-based study, you enter the world of n-dimensional R&D. However, working n-dimensionally has an enormous number of dangers that all too often cause project failure. Two key management activities can avoid many of these dangers—forging a customer/supplier alliance and qualifying the experiment platform.

The R&D department is the supplier of technology, knowledge, and products. In all R&D projects the first order of business is forging an alliance with the customer. R&D's customer will typically be an in-house sales/marketing department or the external consumer of the product.




**Cause-and-effect diagram for composite production is valuable for identifying the main effectors of product quality and performance.**

The alliance is created by negotiating "reasonable" goals in terms of expected completion dates, product requirements, number of concurrent projects, or any combination thereof. For R&D, unreasonable goals are the principal sources of customer/supplier conflicts.

The basis for success in this negotiation is quantitation. That is, R&D must guide the customer in expressing all project goals in quantitative terms. For example, a given current product has a tensile strength of 300 MPa. The customer needs a "stronger" product—a qualitative specification. But a goal of stronger is a moving target. What may be an acceptable improvement in tensile strength today may not be so two months into the project. So R&D must guide the user to quantify "how much stronger."

Quantifying the goal is done by proposing numbers that first bracket the goal, then narrow in on a single target. For example, given a current 300 MPa, R&D can ask whether 325 MPa is an acceptable improvement, or whether as much as 350 MPa is required. Within this 50 MPa bracket, both parties must settle on an appropriate single target. There may even be a question of whether the current materials and process can yield the required improvement. In this case some preliminary work may be necessary before setting the final goals.

Quantified goals are the benchmarks for project completion and customer satisfaction. A successful negotiation of quantified goals builds teamwork and solidarity between R&D and its customer. However, with only qualitative goals, the R&D manager can't know when his or her job is done.

He or she also has no yardstick for assessing how far they are from achieving their goals. The lack of quantified goals is thus a major source of customer dissatisfaction and perceived failure that fuels continued customer/supplier enmity.

Another way to avoid problems is to qualify the experiment platform.

This platform is made up of all the discrete materials, activities (people functions), and processes (equipment functions) involved in preparing and testing prototypes. Each of these discrete elements contains some inherent variation.

Raw materials always vary in quality between batches. The reproducibility of personnel varies between shifts, days, and even before and after lunch. The precision and accuracy of processes and test instruments varies over time. Subjective tests almost always have very poor precision and accuracy. The accumulated variation from these elements is the background noise, or overall experimental error, of the R&D platform.

Qualifying the experiment platform means confirming that the magnitude of overall experimental error is sufficiently small so as to allow you to obtain meaningful experiment data. The question that naturally arises is "how small is sufficiently small?" As a guideline, your overall experimental error is sufficiently small if the response range defined by your three-sigma limits is at most 20% of your expected experiment data range.

R&D personnel sometimes make the mistaken assumption that the precision limits of a given test instrument are equal to the overall experimental error in the associated test data. However, in most cases the instrument is the smallest contributor to overall error. The largest contributors to error are normally the people functions and the process equipment.

The first step in qualifying the experiment platform is flowcharting the platform. An Ishikawa cause-and-effect diagram is easily adapted to this purpose. The traditional use of this diagram is for the graphical arrangement of the "theoretical" causes of a product defect.

The diagram can be adapted to the graphical arrangement of all the discrete elements in the experiment platform. I emphasize the word "all," since typically all of these elements have some contribution to both product quality and overall experimental error. While only a very few of the elements will be addressed in controlled fashion as part of a designed experiment, all of the elements will be at play exercising their respective influences. Thus all these discrete elements must be identified.

A cause-and-effect diagram of a "prepreg" process, for example, can illustrate this effect. Prepreg is resin-impregnated fabric used to make composite materials. These are strong, lightweight materials used to make, among other things, aircraft parts such as jet engine turbine fan blades.

The cause-and-effect diagram should always be constructed by a team of individuals with solid experience in all aspects of the platform. It should therefore include the personnel responsible for raw material certification, the process engineers and operators, and the personnel who conduct product testing.

The team's broad base of knowledge and experience assures that important effectors of product quality and background noise will not be missed.

The importance of the team approach cannot be overstated. Over the years I have lead teams through the exercise of creating such a diagram many times. There has never been a single case in which one individual could have independently constructed a "complete" diagram, i.e., one with no missing effectors.

The second step in qualifying the experiment platform is carrying out a series of qualification runs. These are replicate (repeat) cycles of preparing and testing prototypes. The replicate runs are not simply re-tests of the same prototype. They are complete repeats of the total work involved in making and testing a prototype.

You should prepare and test at least three widely different prototype configurations (five are recommended), and each configuration should be run at least twice. The prototype configurations should differ in the level settings of one or more "key" platform elements selected from the cause-and-effect diagram. You select key elements by ranking all the diagram elements in terms of their relative ability to affect product quality.

You must then develop a strategy for the remaining elements in the experiment platform that minimizes their respective contributions to overall experimental error. For example, the qualification runs (and subsequent designed experiments) may involve multiple operators.

In this case you may need to train the operators in specific sample preparation and testing protocols. This will minimize variation and bias in your data due to differences between operators.

The data from the qualification runs provides an estimate of the overall experimental error inherent in the platform. There is no absolute rule for determining if the platform is "qualified."

As previously stated, you can consider that your platform is qualified if the response range defined by your three-sigma limits is at most 20% of your expected experiment data range. However, your platform is definitely not qualified if your three-sigma limits cover 50% or more of your expected experiment data range.

Qualifying the experiment platform before you carry out a designed experiment is the only way to assure that you are not wasting time and money generating unreliable data. The replicate runs you subsequently carry out as part of a well-designed experiment are used to confirm that the overall data are reliable, i.e., that the error has not increased to unacceptable levels.

Additionally, the replicate data can be translated into numerical analysis targets that define when your data analysis has adequately quantified all your variable effects and can be considered complete.

In the n-dimensional world of DOE, forging a customer/supplier alliance and qualifying the experiment platform are critical up-front management tasks. Quantitative R&D goals keep your project on track. A qualified experiment platform yields reliable data that quickly and surely advances your knowledge and your products. These proven project management techniques will tremendously enhance your opportunity for success with DOE.

***—Richard Verseput***

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