CONCURRENT ENGINEERING

Concurrent engineering (CE) was first defined in the Institute for Defense Analyses Report R-338 (1) printed in 1986. As given in that report, concurrent engineering is

> a systematic approach to the integrated, concurrent design of products and their related processes, including manufacture, and support. This approach is intended to cause the developers, from the outset, to consider all elements of the product life cycle from concept through diposal including quality, cost, schedule, and user requirements.

Implicit in this definition is the concept that in addition to input from the "developers" of the concept, input should come, "from the outset," from end users of the product (customers), from those who install and maintain the product, from those who manufacture the product, and from those who test the product, as well as from the traditional "designers" of the product.

Concurrent engineering is sometimes presented solely as a method used to shorten the time to market for new or improved products. The marketplace has shown that product, even if highly competitive in every other way, must not be late to market, because market share and profitability will be adversely affected (2). Yet, looking to the preceding definition, it is much more: "consider all elements of the product life cycle from concept through disposal." Such input, as appropriate, should be present in all phases of the product life cycle, even the earliest design work.

This concurrent design approach is implemented by bringing together specialists from design, manufacturing, test, procurement, field service, finance, marketing, and so forth, into a team specifically for this product and process and then involving all of the team in the earliest design considerations. It is very different from the procedure so long used by industry. The earlier procedure became known as the over-the-wall process. It was a sequential process. The product concept, formulated at a high level of company management, was passed to a design group. When the design group completed its design effort, it tossed the design over the wall to manufacturing, moving then to an entirely new and different product design and giving no further thought to this previous design. Manufacturing did the best it could with the design and then tossed its product to test, and so on through the chain. The unfortunate result of this sequential process was the necessity for redesign, which happened with great regularity, wasting time and resources as the design process was repeated to correct earlier errors or inadequacies.

Traditional designers too frequently have limited knowledge of a manufacturing process, especially its capabilities and limitations. This may lead to a design that cannot be made economically, cannot be made in the time scheduled, or perhaps cannot be made at all. The same can be said of the specialists in test, marketing, and other processes. The outcome is a redesign effort required to correct the deficiencies found during later processes in the product cycle. Such redesign effort is costly in both economic and time-to-market terms. Another way to view these redesign efforts is that most of them are not *value added.* Value added is a particularly useful parameter by which to evaluate a process or practice (3).

A long-used estimate of the added cost of redesign is that corrections made in a following process step can be up to ten times more costly than correctly designing the product in the present step. If the product should be in the possession of a customer when a failure occurs, the results can be not only the direct costs to accomplish the repair or replacement but also lost future sales as the customer looks elsewhere.

There are two characteristics of concurrent engineering that must be kept in mind at all times. The first is that concurrent engineering is a team effort. This team is more than the customary committee. While it is composed of specialists from various activities, the team members are not there as representatives of their organizational home. They are there to cooperate in the delivery of product to the marketplace by contributing their expertise in the task of eliminating redesign loops. Forming the proper team is critical to the success of most CE endeavors.

The second characteristic is that concurrent engineering is information and communication intensive. There must be no barriers of any kind to complete and rapid communication among all parts of a process, even if located at geographically dispersed sites. If top management has access to and uses information relevant to the product or process, this same information must be available to all in the production chain, including the line workers. An informed and knowledgeable work force at all levels is essential so that workers may use their efforts to the greatest advantage. It has been estimated by some that as little as 10% of the capability of the work force has been utilized, a terrible waste of resource.

Information that must be freely available to the members of the team would include that required for meeting performance criteria, manufacturability, testability, compliance with regulations, service, and repair, all with quality and cost as constant requirements. Such inputs to the design process are sometimes called the "Design for . . ." (the requirement is inserted) (4–6). The product team members, by virtue of their knowledge and expertise, should be able to anticipate and design out most (if not all) possible problems before they actually occur.

The management that assigns the team members must also be the coaches for the team, making certain that the team members have the proper expertise, are properly trained, and are willing to perform as a team. It is important that the team have an understanding and acceptance of the corporate goals and vision so that the team's work is in concert with the larger corporate vision. This is the task of the coaches. It is then that the coaches allow the team to proceed with the project with as little interference but with as much support as is needed. There is no place here for the traditional hierarchy of the past.

An important characteristic of concurrent engineering is that the design phase of a product cycle will nearly always take more time and effort than the original design would have in the serial process. However, most organizations that have used concurrent engineering report that the overall time to market is measurably reduced because product redesign is greatly reduced or eliminated entirely. "Time is money" takes on added meaning in this context.

Concurrent engineering is as much a cultural change as it is a process change. For this reason it is often, unfortunately, achieved with some trauma. The extent of the trauma is dependent on the willingness of people to accept change, which, in turn, is most often dependent on the commitment and sales skills of those responsible for installing the concurrent engineering culture. While it is not usually necessary to reengineer (that is, to restructure) an entire organization in order to install concurrent engineering, it is also true that in many organizations concurrent engineering cannot be installed like an overlay on top of existing structures. Although some structural changes may be necessary, the most important change is in attitude, in culture. Yet it must also be emphasized that there is no "one size fits all" pattern. Each organization must study itself to determine how best to install concurrent engineering. There are some considerations that are helpful in this internal study. Many fine ideas can be found in Salomone (4) and in Carter and Baker (5). The importance of commitment to a concurrent engineering culture at every level, from top management to line workers, cannot be emphasized too strongly.

THE PROCESS VIEW OF PRODUCTION

Ideally, the product cycle becomes a seamless movement through the design, manufacture, test, sales, installation, and field maintenance activities. The CE team has been charged with the entire product cycle such that allocation of resources is seen from a holistic view rather than from a departmental or specialty view. There is no competition within the organization for resources. The needs of each activity are evident to all team members. Although this sounds easy, in the real world of commerce, competing ideas related to implementation of the process are not always easy to resolve. This is where the skills and commitment of team members become very important.

The usual divisions of the process cycle can be viewed in a different way. Rather than discuss the obvious activities of manufacturability, testability, and others, the process can be viewed in terms of a set of functional techniques that are used to accomplish the process cycle. Such a view might be as shown in Fig. 1. In this view, it is the functions of quality function deployment (QFD), design of experiments (DOE), and process control (PC) that are emphasized, rather than the design and other factors. It is the manner in which the processes of design, manufacturing, and so on are accomplished that is described.

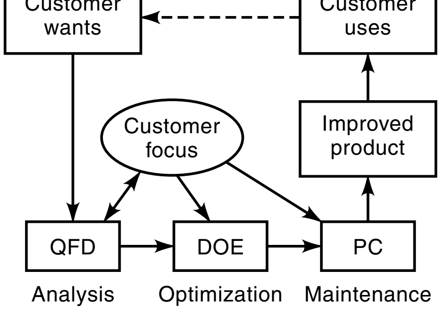


Figure 1. A process cycle description relating QFD to analysis, DOE to optimization, and PC to process maintenance.

QFD is equated with analysis in the sense that the customers' needs and desires must be the drivers in the design of products. Through the use of QFD, not only is the customer input (often referred to as the voice of the customer) heard, it is translated into a process to produce the product. Thus, both initial product and process design are included in QFD in this view. It is important to note that for best effect the product and the process to produce the product are designed together, concurrently.

DOE is equated with optimization and can be used in one of two ways. One way is the optimization of an existing process by identifying and removing any causes of defects, and by determining the best target value and specification limits of the parameters. The purpose of this is to maximize the yield of a process, which frequently involves continuous quality improvement techniques. The second way to use DOE is the optimization of a proposed process before it is implemented. Simulation of processes is becoming increasingly important as the processes become increasingly complex. DOE, combined with simulation, is the problem-solving technique of choice, both for running processes and for proposed processes.

PC is equated with maintenance and is a monitoring process to ensure that the optimized process remains an optimized process. Its primary purpose is to issue an alarm when a process is moving away from its optimized state. Often, this procedure makes use of statistical methods and is then called SPC, statistical process control. When PC signals a problem, problem-solving techniques, possibly involving DOE, must be implemented. The following sections will expand on each of these functional aspects of a product cycle.

QUALITY FUNCTION DEPLOYMENT

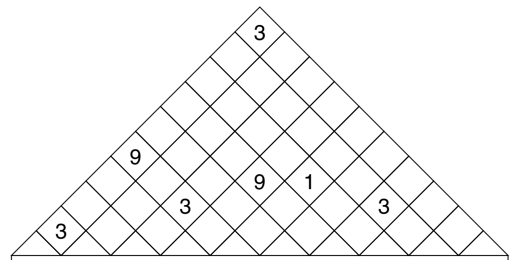
QFD was developed in Japan in the early 1970s and first described in the United States in 1983 in an article by Kogure and Akao (7). Akao also edited a book published in the United States in 1990 (8). In the interim, numerous papers and articles were published, and continue to be published to date.

QFD begins with a determination of the customers' needs and desires. There are many ways that raw data can be gathered. Two of these are questionnaires and focus groups. Obtaining the data is a well-developed field. The details of such techniques will not be discussed here because much has been written on the subject. It is important, however, that professionals are involved in the design of such data acquisition because of the possible errors in constructing the tools and in misinterpreting the data.

The customer data obtained must be translated into language that is understood by the company and its people. It is this translation that must extract the customers' needs and wants and put them in words that the designers, manufacturers, and so on can use in their tasks. Yet the intent of the customers' words must not be lost. This is not always an easy task, but it is a vital one. Another facet of this is the determination of unstated but pleasing qualities of a product that might provide a marketing edge.

House of Quality

Translating the customer's responses into usable items is most often accomplished by application of the house of qual-



CAs \ ECs	A	B	C	D	E	F	G	H	I	J	Importance	Our status	Improvement needed	Competitive advantage		%
1	9		3	3		1					5	3	1.7	1.0	5.1	21
2		3	1			9					3	3	1.0	1.5	4.5	19
3	3	3		1	1		3		9	1	3	4	1.3	1.0	5.2	22
4			1					1			2	3	1.0	1.0	3.0	13
5	1	1			3				1		1	4	1.0	1.5	60	25
6			3			1				3					23.8	100
7				9			3		1							
8	9				3			3								
9		3		1			1			3						
10	3		9													
Total	25	10	20	14	7	11	7	4	11	7	116					
%	21	9	17	12	6	10	6	3	10	6	100					

Figure 2. A sample house of quality showing relationships between CAs and ECs, with a roof showing interactions between ECs and also a planning matrix for evaluating CAs in terms other than ECs.

ity. The house of quality is a matrix or, perhaps more accurately, an augmented matrix. Two important attributes of the house of quality are (1) its capability for ranking the various inputs in terms of perceived importance, and (2) the data in the completed house that show much of the decision making that went into the translation of customers' inputs into usable task descriptions. This latter is often called the archival characteristic and is especially useful when product upgrades are designed or when new products of a similar nature are designed.

A main matrix, the central part of a house of quality, is shown in Fig. 2, with ranking information in the intersecting cells and a summary at the bottom. The inputs are the rows of the matrix, called the customer attributes (CA). The columns are the engineering characteristics (EC) needed to realize the CAs. In this example the ratings of the ECs are assigned only three relative values, 1, 3, and 9, with a blank indicating no importance, rather than a full range of 0 to 9. This is frequently done to reduce the uncertainty and lost time as a result of trying to decide, for example, between a 5 or a 6. Weighting the three levels unequally can give emphasis to the more important relationships.

Following completion of the main matrix, the augmentation portions are added. The first is usually the planning matrix that is added to the right side of the main matrix. Each new column added by the planning matrix lists items that have a relationship to one or more of the CAs but are not ECs. Such items might be assumed customer relative importance, current company status, estimated competitor's status, sales positives, and improvements needed.

Another item of useful information is the interaction of the ECs, because some of these interactions can be positive, reinforcing each other, while others can be negative, such that improving one can lower the positive effect of another. Again, the house of quality can be augmented to indicate these interactions and their relative importance. This is accomplished by adding a roof. This is important information for the design effort, helping to guide the designers as to where special effort might be needed in the optimization of the product.

It is likely that the ECs used in the house of quality will need to be translated into other requirements. A useful way to do this is to use the ECs from this first house as the inputs, like the CAs, to a second house whose output might be cost or parts to accomplish the ECs. It is not unusual to have a sequence of several houses of quality.

The final output of a QFD study should be a product description and a first pass at a process description to produce the product. The product description should be traceable to the original customer inputs so that this product will be competitive in those terms. The process description should be one that will produce a quality product in a competitive time and cost framework. It is important to note that the QFD process, to be complete, requires input from people knowledgeable about all parts of a product cycle.

Experience has shown that initial use of this powerful tool will most likely be more expensive than currently used methods because of the familiarization that must take place. Also, experience has shown that it must be used appropriately. For example, it should not be used for small tasks, those with fewer than about 10 input statements. It should probably not be used if the number of inputs exceeds about 40 because such complexity makes the relative weightings difficult to manage with a satisfactory degree of confidence. Those institutions that have learned to use QFD most often do find it efficient and valuable as well as cost effective and become ardent supporters of its use (9).

DESIGN OF EXPERIMENTS

DOE is an organized procedure for identifying, improving, and optimizing those parts of a process that are resulting in or might be expected to result in less than satisfactory product. The process might be one already in production or it might be one that is proposed for a new product. A complex process cannot be studied effectively by varying one parameter at a time while holding all others fixed. Such a procedure, though taught in most academic classes, where the number of variables is usually small, totally ignores the possibility of interactions between parameters, a condition that often occurs in the real world. However, if all interactions as well as a number of primary parameters are to be tested, the number of experiments required rapidly becomes large enough to be out of the question for more than a few variables (2^n trials for only two levels of n variables). Using DOE will (1) help reduce the number of experiments required to uncover a problem parameter, and (2) ensure the validity of the experimental results.

The following discussion of DOE describes three approaches. The first is the approach of Shainen. It is the easiest to use of the three. It does not require extensive knowledge of mathematics or statistics, although the procedures are based in these disciplines. Nor does it require a mathematical model of the process. The second is the approach of Taguchi, which is a part of a larger system trademarked by the American Supplier Institute (Dearborn, MI) as the Taguchi Methods. The third approach is that of classical statistics. This requires a mathematical model and some sophistication in mathematics and statistics. A technique called response surface methodology is used to find the optimum parameter values.

All three approaches use some basic statistical tools. Among them, ANOVA (analysis of variance) of discrete data of a few parameters can usually be done following a few simple rules, creating charts that can be easily generated and interpreted by nonprofessionals. The study of all parameters and all their interactions, called full factorial analysis, is also used. To guide the experiments, a matrix is used, with factor levels in columns and with rows to specify which levels of the factors are to be used in which experiments. Unfortunately, both of these are time consuming for hand calculations when involving more than about four parameters.

To reduce the number of experiments required, the fractional factorial method of analysis was developed. In this procedure, only primary parameters and a selected set of their interactions are studied. A problem with this technique is that aliasing or confounding occurs because for any two columns representing primary factor levels, a third column is the interaction of these two columns. That third column may also be assigned a primary factor so that the data in that column become a mix of the primary factor data and the interaction data. Nonetheless, this technique is widely used for reducing the number of experiments required. How to select the interactions (that is, which to study and which to omit) can be a problem. Use of brainstorming and other similar techniques from total quality management (TQM) can help but do not remove the nagging questions about those that are left out. Were they left out because of ignorance of them by the team, or because a member of the team dominated the selection but had erroneous ideas?

A technique guiding the selection of parameters for a fractional factorial study was introduced by Genichi Taguchi using orthogonal arrays (OAs), a modification of Hadamard matrices. Use of the technique is not simple and requires more than a passing acquaintance with the method. A shortcoming of the technique is that there are no guidelines for selecting among the possible interactions, much the same as that for the original fractional factorial method. Also, as with fractional factorials, some OA columns inherently contain interaction data that becomes "confounded," mixed additively, with the main parameter data. The response of Taguchi to this criticism is that most problems are due to the main parameters and first studies should include as many main parameters as possible. The assumption is that the interaction data are a small part of the data in a column. Yet this leaves for others the nagging question of the interaction effects that may be important but were confounded or totally excluded. Nonetheless, the successes of the Taguchi Methods are many.

The general procedure to be followed in all three approaches is that of first reducing a large number of possible causes to a few. To do this, the classical and Taguchi procedures rely on brainstorming, whereas Shainen suggests a different procedure, described in the following subsection. Each system relies on full or fractional factorial and ANOVA procedures to assess the relative importance of the factors and to guide the allocation of resources in the improvement of processes. All of them also strive for a reduction of variability of key parameters and the determination of parameter values that are then centered within proper specification limits. Once the culprits have been identified, they can be corrected and optimized so that the process is producing the best product it is capable of producing.

Shainen Approach

This discussion of Shainen's procedures follows closely the descriptions found in the book *World Class Quality* by Keki Bhote (10), an "avowed disciple" of Shainen. Generally, only simple hand calculations are required, plus filling in appropriate tables that "do" the statistics. Application of the techniques requires very little knowledge of statistics.

To begin, only a knowledge of mean, median, and standard deviation is required. It is important to realize that because of the limited knowledge of statistics required to follow the rules to be described, a professional statistician should be available to answer questions that may arise when application is made to systems even slightly different from the simple ones described in the aforementioned book and the discussion here. It is also important to realize that the technique uses only two factor levels (that is, two data points or levels) of the parameters. This assumes that the parameters behave smoothly, even linearly, between and about the two points. This is sometimes an inappropriate assumption and must always be kept in mind when evaluating the results.

Seven different procedures make up Shainen's system. These are shown in Fig. 3. The basic concept is to eliminate as early as possible those variables that can be shown not to be a cause because they are of the wrong type. For example, multi-vari charts (dating from the 1950s) are useful for defining what type, or family, the culprit parameter is, allowing elimination of those parameters that are not in this family. Multi-vari charts may be used with one of the other two shown as first-level procedures, components search and paired comparisons. However, these last two are mutually exclusive. Components search (also a well-known procedure) requires that the product be disassembled and reassembled.

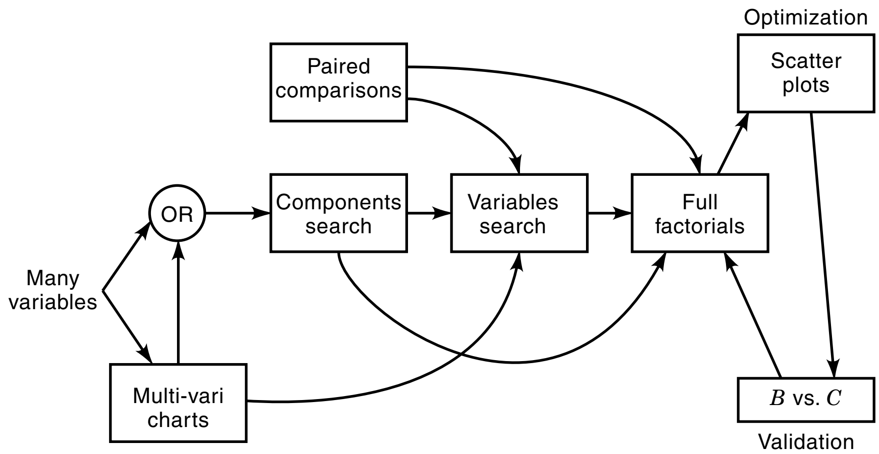


Figure 3. Shainen's system for DOE illustrating possible pathways from initial investigations to confirmed solutions.

Paired comparisons is the method to use if the product cannot be disassembled but must be studied as a unit.

If, after identifying the family of the causes, there are more than four causes, a variables search is done to reduce the number to four or fewer. Once reduced to four or fewer, a full factorial analysis and ANOVA analysis are done to identify the most important parameters and parameter interactions. Corrective action is then taken to bring the offending parameters to their best values and best specification limits. This uses the realistic tolerances parallelogram plots, also called scatter plots. Once the offending parameters are adjusted to the best values, a B versus C, better versus current, comparison experiment is run to confirm that indeed B is better than C. B versus C might also be used before optimization.

Color language was introduced by Shainen to help users remember the methods. The purpose of the procedures is to find the *Red X* or the *Pink X*s. The Red X is the one primary cause with all other possible causes of much lesser importance. If one primary cause cannot be found, then the two or more partial causes that must be considered are called the Pink Xs.

Multi-vari Charts. The multi-vari chart is used to classify the family into which the Red X or Pink Xs fall. A parameter that can be used as a measure of the problem is chosen for study. Sets of samples are then taken and the variation noted. Three comparative categories that might be used to describe the parameter output variation are as follows: (1) Variation within sample sets (called cyclical variation) is larger than variation within samples or variation over time, (2) variation with time (temporal variation) between sample sets is larger than variation within sample sets or variation of the samples, and (3) variation within samples (positional variation) is larger than variation of sample sets over time or variation within the sample sets.

To illustrate, assume a process has been producing defective product at a known historical rate (that is, at an average rate of X ppm) for the past weeks or months. Begin the study by collecting, consecutively, a sample set of three to five products from the process. At a later time, after a number of units have been produced in the interim, collect three to five products again. Repeat this again and again, as often as necessary, three to five times is frequently sufficient, to "capture" at least 80% of the historical defect rate in the samples. That is, these samples should include defects at least at 80% of the historical rate, X, that the process has produced defects in historical samples. This is an important rule to observe, to provide statistical validity to the samples collected. One or two of the aforementioned results should become evident in plots of the data.

This technique is not, therefore, a random selection of samples, as is required in many statistical methods. It also is not a control chart, even though the plot may resemble one. It is a snapshot of the process taken at the time of the sampling. The purpose of this experiment is to determine what families of data can be eliminated from consideration. Further experiments will be necessary to determine the Red X or the Pink Xs from this set.

Components Search. Components search is used when a product can be disassembled and then reassembled. It resembles the parts-swapping procedure that is familiar to many who have done field repair. The first step is to select a performance parameter by which good and bad units can be identified. A good unit is then chosen at random, measured, disassembled, and reassembled two times, measuring the performance parameter each time. These three data points establish a range of variability of the performance parameter, sometimes called the error variance, that is related to the assembly operation for good units. Repeat this for a randomly selected bad unit, once again establishing the range of variability of the performance parameter for assembly of bad units. The good unit must remain a good unit after disassembly and reassembly, just as the bad unit must remain a bad unit after disassembly and reassembly. If this is not the case, or if the difference between a good and a bad unit becomes too small, then the parameter chosen as performance indicator needs to be reviewed.

Because there are only three data points for each type of unit, the first requirement here is that the three performance parameter measurements for the good unit must all yield values that are more acceptable than the three for the bad unit. If this is so, there is only a 1 in 20 chance that this ranking of measurements could happen by accident, giving a 95% confidence in this comparison. The second requirement is that there be a minimum separation between the medians of variability of the good unit and the bad unit. Bhote (10) suggests that this separation, D, exceed $1.25d$, where d is the average of the ranges of the data for the good and bad units. The value of 1.25 for the ratio D/d is based on the classical F Table at the 0.05 level. A more detailed description of the determination of this ratio, 1.25 for this example, is given in a paper by D. Shainen and P. Shainen (11). Meeting this requirement, the results of further tests conducted by swapping parts have at least a 95% level of confidence in the results.

Using the data from the disassembly and reassembly, control limits for performance, good and bad units, are calculated and plotted on a chart. Bhote (10) suggests that the control limits be calculated by

$$\text{limits} = \text{median} \pm 2.776d/1.81 (\text{statistics done using the student's t-distribution for 95\%})$$

As parts are swapped between units, the results are plotted on this same chart.

Three results are possible for units with swapped parts: (1) The part stays within its control limits, indicating that the part is not at fault; (2) a change in at least one of the units outside its limits but not a complete reversal, indicating a Pink X; or (3) the units flip-flop, a complete reversal within control limits, the good unit becoming a bad unit and vice versa, indicating a part that is seriously at fault (the Red X). A Pink X is a partial cause, so that one or more additional Pink Xs should be found. Finally, if several Pink Xs are found after swapping all parts, they should be bundled together (that is, all the parts with a Pink X result should be swapped as a block between units). This is called a confirmation experiment or capping run. A capping run should result in a complete reversal, indicating that there are no other causes. Less than a full reversal indicates that other, not identified, causes exist or the performance measure is not the best that could have been chosen.

If a single cause, a Red X, is identified, the experiments are over and corrective action can be taken. If two to four Pink Xs are found, a full factorial analysis, described later, should be done to determine the relative importance of the revealed causes and their interactions. If more than four Pink Xs are found, a variables search is the next step.

Paired Comparisons. If the product cannot be disassembled and reassembled, the technique to use is paired comparisons. Select pairs of good and bad units and compare them, using whatever visual, mechanical, electrical, or chemical comparisons are possible, recording whatever differences are noticed. Do this for several pairs, continuing until a pattern of differences becomes evident. In many cases, a half dozen paired comparisons is enough to detect repeatable differences. The units chosen for this test should be chosen at random, using a random number table, to establish statistical confidence in the results. If the number of differences detected is more than four, then use of variables search is indicated. For four or fewer, a full factorial analysis can be done.

Variables Search. Variables search is best applied when there are five or more variables with a practical limit of about 20. The purpose is to reduce the number of variables to four or fewer so that a full factorial analysis can be done. Variables search begins by determining a performance parameter and defining two levels of result, a best and a worst. Then a ranking of the variables as possible causes is done (using brainstorming, etc.), with the first being deemed the most likely. The idea is that the culprit should be found as quickly as possible to reduce the total number of experiments. Next, assign for each variable two levels (call them best and worst or good and bad or some other distinguishing pair), even if the best is not actually known to be the best.

For all variables simultaneously at their assigned best level, the expected result is the best for the performance parameter chosen, similarly for the worst levels. Run two experiments, one with all variables at their best levels and one with all variables at their worst levels. Do this two more times, randomizing the order of best and worst combinations. Use this set of data in the same manner as that for components search using the same requirements and the same limits formula.

If the results meet the best and worst control limits performance criteria, proceed to the next step. If the results do not meet these requirements, interchange the best and worst levels of one parameter at a time until the requirements are met or until all pair reversals are used. If the requirements are still not met, an important factor has been left out of the original set and additional factors must be added until all important requirements are met.

When the requirements are met, then proceed to run pairs of experiments, choosing first the most likely cause and exchanging it between the two groupings. Let the variables be designated as A, B, and so on, and use subscripts B and W to indicate the best and worst levels. If A is deemed the most likely cause, then this pair of experiments would use $A_W R_B$ and $A_B R_W$, R standing for all remaining variables, B, C, and so on. Observe whether the results fall within the limits, outside the limits but not reversal, or complete reversal, as before. Use a capping run if necessary. If the Red X is found, proceed to remedial efforts. If up to four possible culprits are found, proceed to a full factorial analysis.

Full Factorial Analysis. After the number of possible causes has been reduced to four or fewer but more than one, a full factorial analysis is used to determine the relative importance of these variables and all their interactions. Once again, the purpose of DOE is to direct the allocation of resources in the effort to improve a product and a process. One important use of the results is to open tolerances on the lesser important variables if there is economic advantage in doing so.

The simplest four-factor factorial analysis is to use two levels for each factor, requiring that 16 experiments be performed in random order. Actually, for reasons of statistical validity, it is better to perform each experiment a second time to allow for "noise" and measurement tolerances to enter the data, again performing the second 16 experiments in a different random order, requiring a total of 32 experiments. If there are fewer than four factors, then correspondingly fewer experiments would need to be performed. The data from these experiments are used to generate two charts, a full factorial chart and an ANOVA chart. Examples of these two charts for a four-parameter case are shown in Figs. 4 and 5, where the factors are A, B, C, and D with the two levels denoted by $+$ and $-$. The numbers in the circles represent the average or mean of the data for the two performances of that particular combination of variables. These numbers are then the data for the input column of the ANOVA chart. The numbers in the upper left corner are the cell or box number corresponding

	A+*B*+	*A*+*B*−	*A*−*B*−	*A*−*B*+		
C+*D*−	8: 15, 17 (17)	6: 14, 20 (17)	5: 88, 98 (93)	7: 6, 10 (8)	135	*A*+ = 204, *A*− = 203
C+*D*+	16: 18, 22 (20)	14: 32, 42 (37)	13: 2, 10 (6)	15: 0, 0 (0)	63	*B*+ = 98, *B*− = 309
C−*D*+	12: 6, 12 (9)	10: 53, 61 (57)	9: 63, 77 (70)	11: 8, 12 (10)	146	*C*+ = 198, *C*− = 209
C−*D*−	4: 26, 30 (28)	2: 24, 14 (19)	1: 10, 10 (10)	3: 4, 8 (6)	63	*D*+ = 209, *D*− = 198
	74	130	179	24		

Figure 4. A four-factor, two-level, full factorial example indicating row and column summations to discover the relative importance of the factors by the difference between the + and − sums, a large difference indicating importance.

to the cell number in the left-hand column of the ANOVA chart.

In the ANOVA chart, the + and − signs in the boxes indicate whether the output of that row is to be added to or subtracted from the other outputs in that column, with the sum given at the bottom of that column. A column sum with small net, plus or minus, compared to other columns is deemed to be of little importance. The columns with large nets, plus or minus, are deemed the ones that require attention. These two charts contain the data necessary to make a determination of relative importance and therefore resource allocation.

Realistic Tolerances Parallelogram Plots. The next step in this set of DOE procedures is the optimization of the variables of the process. Shainen's tool for this is the realistic tolerances parallelogram plot, often called the scatter plot. The purpose is to establish the variables at their optimum target values centered within proper specification limits.

The procedure begins by acquiring 30 output data points by varying the variable over a range of values that is assumed to include the optimum value. Then the output for these 30 data points is plotted versus the variable under study. An ellipse can be drawn or visualized around the data plot to identify a major axis. Two lines parallel to the major axis of the ellipse are then drawn on either side of the ellipse to include all but one or one and one-half of the data points (to allow for an outlier). Specification limits for the output are drawn on the plot. Then vertical lines are drawn to intersect these specification limit lines at the same point that the parallelogram lines intersect the specification limits, as shown in Fig. 6. The intersection of these vertical lines with the variable axis determines the realistic tolerance or specification limits for the variable, with the target value centered within these limits. A possible drawback to this procedure is the number of data points required.

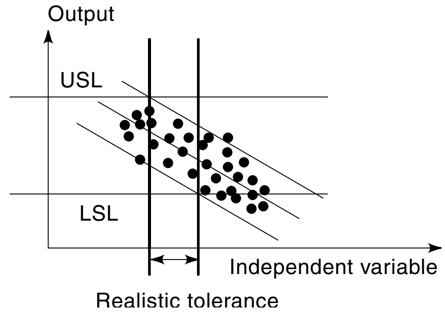


Figure 6. An example of the realistic tolerance parallelogram plot showing 30 data points from which the desired tolerance limits can be found.

Cell	Factors				2-Factor interactions						3-Factor interactions				4-Factor	Output
group	*A*	*B*	*C*	*D*	*AB*	*AC*	*AD*	*BC*	*BD*	*CD*	*ABC*	*ABD*	*ACD*	*BCD*	*ABCD*	
1	−	−	−	−	+	+	+	+	+	+	−	−	−	−	+	10
2	+	−	−	−	−	−	−	+	+	+	+	+	+	−	−	19
3	−	+	−	−	−	+	+	−	−	+	+	+	−	+	−	6
4	+	+	−	−	+	−	−	−	−	+	−	−	+	+	+	28
5	−	−	+	−	+	−	+	−	+	−	+	−	+	+	−	93
6	+	−	+	−	−	+	−	−	+	−	−	+	−	+	−	17
7	−	+	+	−	−	−	+	+	−	−	−	+	+	−	+	8
8	+	+	+	−	+	+	−	+	−	−	+	−	−	−	−	17
9	−	−	−	+	+	+	+	−	−	−	−	+	+	+	−	70
10	+	−	−	+	−	−	+	+	−	−	+	−	−	+	+	57
11	−	+	−	+	−	+	−	−	+	−	+	−	+	−	+	10
12	+	+	−	+	+	−	−	+	+	−	−	+	−	−	−	9
13	−	−	+	+	+	−	−	−	−	+	+	+	−	−	+	6
14	+	−	+	+	−	+	−	+	−	+	−	−	+	−	−	37
15	−	+	+	+	−	−	+	−	+	+	−	−	−	+	−	0
16	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	20
Sums	1	−211	−11	11	99	−33	73	−5	−51	−155	49	−97	163	175	−95	

Key: (+)(+)=+, (−)(−) = +, (+)(−) = (−)(+) = −

Figure 5. An ANOVA chart displaying the four factors of Fig. 4 and all possible interactions with large column sums, plus or minus, indicating large contributions to the problems.

B versus C. An independent experiment to validate these DOE findings is the *B* (better) versus *C* (current) procedure. There are two parts to this validation: (1) ranking a series of samples to see if *B* is better than *C*, and (2) determining the degree of risk of assuming that the results are valid. As before, if there are three *B*s and three *C*s, then requiring that the three *B*s outrank the three *C*s has only a 1 in 20 probability of happening by chance, a 5% risk. These risk numbers are simply the calculation of the number of combinations of the inputs that can result in the required ranking versus the total number of combinations that exist. This risk is called the α risk, the risk of assuming improvement when none exists. This is also referred to as a Type I error risk. There is also a β risk that is the risk of assuming no improvement when improvement actually does exist, referred to as a Type II error risk. Bhote (10) gives a table from Shainen Consultants, Inc. that shows the sample sizes and risks associated with a desired separation of the means of *B* and *C* Gaussian processes. It is worthy of note that decreasing one type of risk increases the other for a given sample size. Increasing the sample size may permit decreasing both. It is also true that increasing the sample size may allow some overlap in the *B* versus *C* ranking (that is, some *C*s may be better than some *B*s in a larger sample size). Please refer to the references for further discussion.

The Shainen techniques presented here are intended to be easy to implement with pencil and paper. Most of the required statistics has been included in the formulas and procedures so that only a minimal background in statistics is required. However, the advice and direction of a professional statistician is always to be considered, especially for complex problems.

Taguchi Procedures

Dr. Genichi Taguchi (12) developed a system of quality improvement that organizes classical statistical methods into a coherent set of procedures that have robust design as the desired end. Robust design is defined simply as system design that is as insensitive to external influences, such as environmental factors or operator differences, as is possible. In the classical sense, design of experiments consists of investigating all factors and all possible interactions of these factors, called full factorial experiments. Recognizing that in a practical situation this often is much too expensive in terms of time and resources, classical methods turned to fractional factorials to reduce the costs.

Fractional factorial experiments use one-half or one-quarter or fewer experiments by selectively leaving out certain factor levels and some or all of the interactions. From a purely mathematical view, there are no rules for which factors or interactions to leave out. Taguchi selected certain of the fractions and developed sets of OAs, matrices with factor levels in factor columns and with experiment runs as rows showing the factor level of each factor to be used in each experiment.

Orthogonal Arrays. Orthogonal in simplest terms means the independence of all factors. Within the OAs, the factors used may have two or three or even more levels that enter into the array rows, one level per row, in such a way that every factor column has all levels an equal number of times. To complete the orthogonality, each factor has its levels in its column in a different order from that of the other factor columns. Combining these requirements, influences of factors on other factors in effect cancel when all experiments are run. This also determines the number of experiments, the rows, in the array. By dictating which factor values are assigned to which rows in the arrays, different experimenters using orthogonal arrays will be able to compare results because they followed the same set of procedures. This is a major contribution of the Taguchi procedures.

Examples of orthogonal arrays in Figs. 7 and 8 show how the rows and columns are organized. A two-level, three-factor array, called L4, and a three-level, four-factor array, called L9, are the simplest to show these ideas. The number after the L indicates the number of experiments required and therefore the number of rows in the OA.

As with fractional factorials, given any two factor columns, a third column will contain the interaction of the first two factors. Thus, a decision must be made as to whether or not to place a third factor in this third column, which will then be summed, or confounded, with the interaction of the other two factors. The results, then, of that column cannot be separated into a main factor and an interaction of two other columns. Many, including Taguchi, believe that for a first set of experiments, it is better to include as many factors as possible and ignore interactions on the assumption that interaction contributions are often far smaller than factor contributions. If that is not the case, then additional experiments will be required, but if it is the case, better information is obtained by including the additional factors.

For an OA having more columns, Taguchi has a set of linear graphs and a triangular table that give the interaction column locations. Excellent discussions of OAs and these tools

L4 (3 factors at 2 levels, 4 experiments)

	Factors			
Exp #	*A*	*B*	*C*	Results
1	1	1	1	
2	1	2	2	
3	2	1	2	
4	2	2	1	

Figure 7. An L4 OA for three factors at two levels, showing the level of each factor to be used in each of the four experiments.

L9 (4 factors at 3 levels, 9 experiments)

	Factors				
Exp #	*A*	*B*	*C*	*D*	Results
1	1	1	1	1	
2	1	2	2	2	
3	1	3	3	3	
4	2	1	2	3	
5	2	2	3	1	
6	2	3	1	2	
7	3	1	3	2	
8	3	2	1	3	
9	3	3	2	1	

Figure 8. An L9 OA for five factors at three levels each, showing the level of each factor to be used in each of the nine experiments.

and those described below can be found in Roy (13) and Ross (14).

Outer Arrays and Noise. In addition to factors that are specifically controlled in an experiment, there are other factors that cannot be controlled or are deliberately not controlled because of the cost or some other reason. Sometimes these, such as environmental conditions, can have an important effect on the outcome of an experiment or product application. Taguchi calls these noise. If they are considered to have an effect and if they can be identified either by measurement or by quality, then Taguchi adds an array, called the outer array, to include their effects. If an L8 is the chosen OA and three noise sources are to be included, then the outer array will include four combinations or columns. A complete study of the original L8 and outer array for three noise sources with four columns will require 32 experiments, called a crossed array study. The purpose of this added noise array is to find the levels of the main factors that reduce the variation of the product in the presence of noise. The levels of factors to reduce noise effects may well be different from the levels found when the noise is ignored. Thus, the purpose is to increase the robustness of the product.

Signal-to-Noise Ratio. To better summarize the results of the outer array analysis, Taguchi introduced the signal-to-noise ratio (SNR), defined much the same as that used in communications. For the target being in the center of specification limits, often called the nominal is best, the SNR is given by

$$\mathrm{SNR} = -10\log_{10} s^2$$

where s^2 = the sample variance = $\Sigma[(y_i - y_{\mathrm{avg}})^2/(n - 1)]$ summed over n points.

For the smaller is better and larger is better, similar formulas can be found in Roy (11) and Ross (12). One unfortunate characteristic of SNR is that widely differing signal shapes can have the same SNR.

Taguchi's Loss Function. Another contribution by Taguchi is the loss function. The usual design specifications for a factor will give limits on the variability of the product or process. Historically, a product that tested within these limits was accepted, as a part of an assembly or a finished product (limits might be less than or greater than a single value). This became known as the "goal posts" concept of specifications, in which any value between the limits is acceptable. However, experience has shown that product that is near the specification limits often will have less life and generate more complaints of less than satisfactory performance than product that has small variability around a target value that is centered within the specification limits, assuming the specification limits have been properly set.

Taguchi suggests that product that does not meet the target value represents a loss to society as well as to the immediate customer and producer. He therefore proposes the loss function that places a square law loss value on the deviation from the target value, as

$$L(Y) = k(Y - Y_0)^2$$

where Y is the actual value, Y_0 is the target value, and k is a constant that depends on the cost of replacement or repair or a similar cost factor. The ideal is that the target value is centered within the specification limits. Such an idea places great emphasis on reduction of variability, an important factor in the quality of a product. For the cases in which more is better or less is better, slight modifications of the loss function can be made.

Classical Design of Experiments

Classical design of experiments is based in statistics. As such, it requires a mathematical model of the process. The model may be derived from data by performing a curve fitting, either a multiple linear regression or a regression for a higher-order model such as a quadratic model containing squares of the factors as well as linear terms. Once a mathematical model has been determined, the method of steepest ascent (or descent) can be applied.

For example, for two variables there is a three-dimensional surface representing all values of the function of the two variables within a given range of each variable. This surface, called a response surface, has led to the name response surface methodology for this approach to design of experiments. Myers and Montgomery, in *Response Surface Methodology* (15), present a thorough exposition of this process. Maximizing the derivative can be used to find the direction to be moved on the three-dimensional surface that represents the best path to the optimum values of the two variables. Hypersurfaces are used for more than two variables, but the procedure is the same, if more complicated.

In some respects, the classical approach can be thought of as an extension of the approaches described previously. Perhaps more accurately, the procedures were developed to try to simplify DOE for those not formally trained in statistics. A classical DOE most likely would use two-level experiments assuming a linear relationship between variables to "home in" on the regions where the higher-order mathematical tools can be used to find the optimum. The tools of factorial design and ANOVA as described previously are required procedures. However, in many practical applications, finding the absolute optimum values for the variables is not the best option because of the cost. Then the approaches that find acceptable improvements are selected, such as a truncated classical or those of Shainen or Taguchi. Nonetheless, the classical approaches do provide the optimum target values compared to the results from Shainen and Taguchi, which provide only the best combination from a selected set of discrete values that may or may not include the actual optimal values.

Recognizing the problems that historically limited the usefulness of the classical methods, statisticians have developed additional tools to lessen these effects. Techniques such as blocking, using central composite design, and several others have been used to improve the performance/cost ratio for classical design of experiments. These are beyond the scope of this discussion but should be a part of any studies using classical design of experiments. Many of these techniques are also discussed in Myers and Montgomery (15).

Process Control

Process control is used to maintain the process conditions determined by design of experiments. It accomplishes this by detecting when a process is going "out of control." Historically this has been done by plotting a control chart on which control limits are marked and data points from the process are plotted. Control limits are found by taking data, determining the average values and the range of values of the data, and then applying specific formulas to calculate the control limits. Data points inside the limits indicate satisfactory performance, while data points outside the control limits indicate unsatisfactory performance. But data points outside the acceptable values come from a process already out of control. It would be much better to anticipate an out-of-control condition and prevent it if possible. To this end, a number of techniques have been developed, such as dividing the region between the control limits into subregions and following trends or movement within these regions. Many of these are described in the article PROCESS CONTROL. In the following, a less well-known technique, due to Shainen, will be described, but first a definition of process capability will be helpful.

Process Capability. The capability of a process is defined in terms of the specification limits (goal posts) and the actual process performance itself. Variation in many processes in manufacturing can be described well by the normal or Gaussian distribution curve, with its mean value, μ, and standard deviation, σ. Traditionally, a standard deviation of $\pm 3\sigma$ has been used in manufacturing as the acceptable range of values around the mean value. The definition of process capability is:

$$C_p = (\text{specification range})/(\text{process range})$$

For a process with a mean centered within the specification limits, the $C_p = 1.0$ if the $\pm 3\sigma$ process limits coincide with the specification limits. While this was an acceptable number for many years, giving about 2600 ppm total error rate for a centered process, today's competition requires a much better process for survival. The tail outside the specification limits represents the out-of-control or unacceptable product. Recognizing this, the Motorola Company instituted the "6 sigma" definition. This takes into account the inherent variability of real-world processes by allowing the center of the process to move one and one-half a standard deviation, 1.5σ, on either side of center. A Gaussian distribution moved 1.5σ to one side of the center of the specification region results in the Gaussian 6σ intersection, with the specification limit on that side being at a 3.4 ppm error rate (the other tail intersection is so far down that it can be ignored). For such a noncentered process, the process capability is defined slightly differently as

$$C_{pk} = (1 - K)C_p$$

where K = (the off-center distance to the mean)/(one-half the specification width). Thus, the Motorola 6σ process definition results in a $C_{pk} = 0.5C_p$. Also note that a centered 6σ process has an error rate of about 2 ppb (parts per billion), for a $C_p = 2.0$. Shainen suggests that even larger C_p's are possible.

Precontrol. Shainen defined a different chart and its interpretation, called precontrol, to detect a process that is still in control but is heading to out of control. Bhote (10) describes this process, and the following discussion draws heavily on that description. Assume that the process mean is centered within the specification limits, as it should be after design of experiments. The width between the specification limits is divided into four equal regions, two above and two below the mean. The two regions in the center adjacent to and above and below the mean are labeled the green zone. The boundaries of the green zone are called the precontrol lines or limits. The two regions above and below the green zone but inside the specification limits are called the yellow zones. Outside the specification limits are the red zones. The green zones give a $C_p = 2.0$.

Following a set of rules for sampling the process output, a new process can be qualified for production or an ongoing process can be continued without change or with modifications, depending on where the product samples fall, into which zones. It is said that this method is quicker and more accurate and requires fewer samples to detect a process going out of control than the typical control chart methods. The rule is that the longer a process remains in control, the longer the time between samples, requiring fewer samples per unit time for good processes yet penalizing poor processes by requiring more frequent samples. The longer the sample times required, the less costly the process.

As with all processes, there is risk in assuming anything. Bhote (10) suggests that in precontrol, the risk of stopping a good process, the α risk, is about 2% and the risk of not stopping a process that requires modification, the β risk, is about 1.5%. Because of the simplicity of monitoring a process using precontrol, it is easy for most line workers to learn its application to their work, thus making the line worker a quality contributor, not just an observer or data gatherer (16).

CONCLUDING COMMENTS

The use of recently developed software programs is gaining acceptance. Some of these programs are able to do sophisticated data manipulation and plotting. Most use or are closely related to the classical statistical methods. These software programs are not discussed here but should be investigated by anyone planning DOE studies. As mentioned frequently, the advice or direction of a professional statistician is always to be considered, especially for complex problems.

Following the procedures discussed in this article, the process will now be producing the best product it is designed to produce. This product will go to the customer for use. The customer becomes a source of input to the cycle of product and process development for an improved product or a new product based on this product, as shown in Fig. 1. The cycle begins again with QFD.

Disposal of the worn-out or obsolete product is not discussed here because this phase is not at this time being implemented to any degree. The future application of concurrent engineering will undoubtedly include product disposal as part of the design as well as a final step in product life.

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Reading List

M. Brasard and D. Ritter, *The Memory Jogger,* Methuen, MA: GOAL/QPC, 1994.

This pocket sized handbook describes 24 tools for continuous improvement and effective planning with many examples to illustrate their use.

B. King, *Better Designs in Half the Time,* Methuen, MA: GOAL/QPC, 1989.

The GOAL/QPC offers a wide variety of pertinent publications on quality related topics, many written by staff members and many by other well-known authors.

L. Miller, *Concurrent Engineering Design,* Dearborn, MI: SME, 1993.

G. Taguchi and Y. Wu (eds.), *Taguchi Methods,* Dearborn, MI: American Supplier Institute, 1989.

This is a seven-volume series that describes in great depth Taguchi's techniques and includes case studies from Europe and the United States.

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