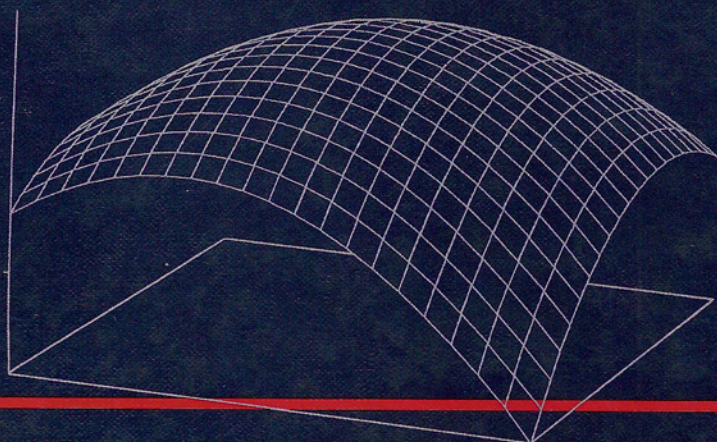

Response Surface Methodology

Process and Product
Optimization Using Designed
Experiments

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WILEY SERIES IN
PROBABILITY AND STATISTICS

Continuous Process Improvement with Evolutionary Operation

13.1 INTRODUCTION

Response surface methodology is often applied to pilot plant operations or in a process development environment by research and development personnel. When it is applied to a full-scale production process, it is usually only done once (or relatively infrequently) because the experimental procedure is relatively elaborate. However, conditions that were optimum for the pilot plant may not be optimum for the full-scale process. The pilot plant may produce a small amount of product per day, whereas the full-scale process will produce much larger quantities. This "scale-up" of the pilot plant to the full-scale production process usually results in distortion of the optimum conditions. Furthermore, actual process equipment may differ in many respects from the pilot or prototype production process. Even if the full-scale plant begins operation at the optimum, it will eventually "drift" away from that point because of variations in raw materials, environmental changes, and operating personnel.

Box (1957) proposed **evolutionary operation (EVOP)** as a method for continuous monitoring and improvement of a full-scale process with the objective of moving the operating conditions toward the optimum or following a "drift." EVOP does not require large or sudden changes in operating conditions that might disrupt production. It was proposed as a method of routine plant operation that is carried out by manufacturing or operating personnel with minimum involvement of the engineering or development staff.

EVOP consists of systematically introducing small changes in the levels of the process variables under consideration. Usually, a 2^k design is employed to do this. The changes in the variables are relatively small, so that serious disturbances in yield, quality, or product characteristics will not occur, yet they must be large enough for potential improvements in process performance to eventually be discovered. Data are collected on the response variables of interest at each point of the 2^k design. When one observation

has been taken at each design point, a cycle is said to have been completed. The effects and interactions of the process variables are then computed. Eventually, after several cycles, the effect of one or more process variables or their interactions may appear to have a significant effect on the response. At this point, a decision may be made to change the basic operating conditions to improve the response. When improved conditions have been detected, a phase is said to have been completed.

In testing the significance of process variables and interactions, an estimate of experimental error is required. In the original version of EVOP proposed by Box, this error estimate is calculated from the cycle data using a range method. Also, the 2^k design is usually centered about the current best operating conditions. By comparing the response at this point with the 2^k points in the factorial portion, we may check on **curvature** or, as it is sometimes called, **change in mean** (CIM). If the process is really centered at the maximum, say, then the response at the center should be significantly greater than the response at the 2^k peripheral points.

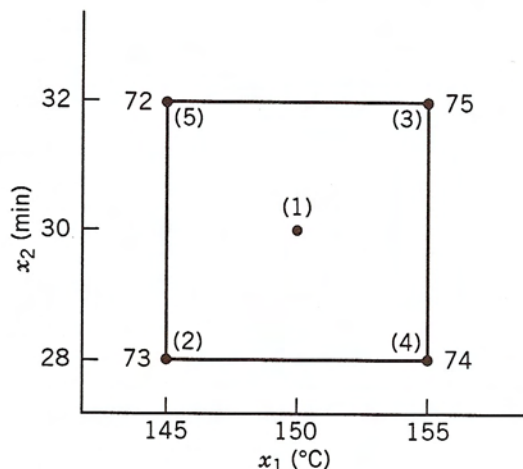
In theory, EVOP can be applied to k process variables. In practice, only two or three variables are usually considered. In the next section, we will give a two-variable example of the original version of EVOP, as proposed by Box (1957). Box and Draper (1969) give a detailed discussion of the three-variable case, including necessary forms and worksheets. Then we will discuss how EVOP can be implemented using modern computer software. Finally, we will discuss a variation of EVOP based on the simplex design, and we will give some advice about the practical implementation of EVOP.

13.2 AN EXAMPLE OF EVOP

We will illustrate EVOP using a chemical process whose yield is a function of temperature (x_1) and reaction time (x_2). The current operating conditions are $x_1 = 150^\circ\text{C}$ and $x_2 = 30$ min. The EVOP procedure uses the 2^2 design plus the center point shown in Figure 13.1. Notice that each of the five points in the design are numbered. The cycle is completed by running each design point in numerical order (1, 2, 3, 4, 5). This run order is used because it is easy for operating personnel to remember. Furthermore, if there are time or other nuisance factor effects, this run order confounds these effects with blocks. The yields in the first cycle are shown in Figure 13.1.

The yields from the first cycle are entered in the EVOP calculation sheet, shown in Table 13.1. At the end of the first cycle, no estimate of the standard deviation can be made. The effects and interaction for temperature and pressure are calculated in the usual manner for a 2^2 design.

A second cycle is then run and the yield data are entered in another EVOP calculation sheet, shown in Table 13.2. At the end of the second cycle, the experimental error can be estimated and the estimates of the effects can be compared to approximate 95% (two standard deviation) limits. Note that "range," shown on the right-hand side of the worksheet refers to the range of

Figure 13.1 A 2^2 design for EVOP.Table 13.1 EVOP Calculation Sheet, $n = 1$

.1	Cycle: $n = 1$ Response: Yield	Phase: 1 Date: 3/27/94
Operating Conditions	Calculation of Averages	Calculation of Standard Deviation
	(1) (2) (3) (4) (5)	
(i) Previous cycle sum		Previous sum $S =$
(ii) Previous cycle average		Previous average $\bar{S} =$
(iii) New observations	74 73 75 74 72	New $S = \text{range} \times$
(iv) Differences [(iii) - (ii)]		$f_{5,n} =$
(v) New sums [(i) + (iii)]	74 73 75 74 72	Range of (iv) =
(vi) New averages [$\bar{y}_i = (v)/n$]	74 73 75 74 72	New sum $S =$
		New average $\bar{S} =$
		New sum S
		$n - 1$
Calculation of Effects		Calculation of Error Limits
Temperature effect		
$= \frac{1}{2}(\bar{y}_3 + \bar{y}_4 - \bar{y}_2 - \bar{y}_5) = 2.00$		For new average $\frac{2}{\sqrt{n}}\bar{S} =$
Time Effect		
$= \frac{1}{2}(\bar{y}_3 + \bar{y}_5 - \bar{y}_2 - \bar{y}_4) = 0.00$		For new effects $\frac{2}{\sqrt{n}}\bar{S} =$
Interaction effect		
$= \frac{1}{2}(\bar{y}_2 + \bar{y}_3 - \bar{y}_4 - \bar{y}_5) = 1.00$		
Change-in-mean effect		
$\frac{1}{3}(\bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5 - 4\bar{y}_1) = -0.40$		For change in mean $\frac{1.78}{\sqrt{n}}\bar{S} =$

Table 13.2 EVOP Calculation Sheet, $n = 2$

53 .1 24	Cycle: $n = 2$ Response Yield	Phase: 1 Date: 3/27/94
Operation Conditions	Calculation of Averages (1)(2)(3)(4)(5)	Calculation of Standard Deviation
(i) Previous cycle sum	7473757472	Previous sum $S =$
(ii) Previous cycle average	7473757472	Previous average $\bar{S} =$
(iii) New observations	7271767573	New $S = \text{range} \times f_{5,n} = (3.6)(0.3) = 0.90$
(iv) Differences [(iii) - (ii)]	-2-2-111	Range of (iv) = 3.0
(v) New sums [(i) + (iii)]	146144151149145	New sum $S = 0.90$
(vi) New Averages	737275.574.572.5	New average $\bar{S} = \frac{\text{New sum } S}{n - 1} = 0.90$
$[\bar{y}_i = (v)/n]$		
Calculation of Effects		Calculation of Error Limits
Temperature effect		For new average $\frac{2}{\sqrt{n}} \bar{S} = 1.27$
$= \frac{1}{2}(\bar{y}_3 + \bar{y}_4 - \bar{y}_2 - \bar{y}_5) = 2.75$		
Time effect		For new effects $\frac{2}{\sqrt{n}} \bar{S} = 1.27$
$= \frac{1}{2}(\bar{y}_3 + \bar{y}_5 - \bar{y}_2 - \bar{y}_4) = 0.75$		
Interaction		
effect $= \frac{1}{2}(\bar{y}_2 + \bar{y}_3 - \bar{y}_4 - \bar{y}_5) = 0.25$		
Change-in-mean effect		For change in mean $\frac{1.78}{\sqrt{n}} \bar{S} = 1.13$
$= \frac{1}{5}(\bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5 - 4\bar{y}_1) = 0.50$		

the differences in row (iv); thus the range is $+1.0 - (-2.0) = 3.0$. This range is converted into s , an estimate of the process standard deviation, by multiplying the range times the factor $f_{5,n} = f_{5,2} = 0.30$ from Table 13.3. The estimate of the standard deviation from each cycle is averaged with the standard deviation estimate from previous cycles through the calculation

$$\text{New average } \bar{s} = \frac{\text{new sum } s}{n - 1}$$

Table 13.3 Values of $f_{k,n}$

$n =$	2	3	4	5	6	7	8	9	10
$k = 5$	0.30	0.35	0.37	0.38	0.39	0.40	0.40	0.40	0.41
9	0.24	0.27	0.29	0.30	0.31	0.31	0.31	0.32	0.32
10	0.23	0.26	0.28	0.29	0.30	0.30	0.30	0.31	0.31

This new average $\bar{s}$ is then used in the calculation of the error limits in the bottom half of the worksheet.

Notice that at the end of the second cycle the temperature effect exceeds its error limit. This is equivalent to the effect estimate differing from zero by at least two standard deviations, so a change in operating conditions is warranted. Because the temperature effect is positive, we should increase temperature in order to increase yield. Therefore, a reasonable strategy would be to begin a new EVOP phase around the point $x_1 = 155^\circ\text{C}$ and $x_2 = 30$ min.

An important aspect of EVOP is feeding the information generated back to the process operators and supervisors. This is accomplished by a prominently displayed EVOP information board. The information board for this example at the end of cycle 2 is shown in Figure 13.2.

Most of the quantities on the two-variable EVOP worksheet follow directly from the analysis of the 2^k factorial design. For example, the variance of any effect estimate, such as time $= \frac{1}{2}(\bar{y}_3 + \bar{y}_5 - \bar{y}_2 - \bar{y}_4)$, is found as follows:

$$\begin{aligned}\text{Var}(\text{Time}) &= \text{Var}\left[\frac{1}{2}(\bar{y}_3 + \bar{y}_5 - \bar{y}_2 - \bar{y}_4)\right] = \frac{1}{4}\left(\frac{\sigma^2}{n} + \frac{\sigma^2}{n} + \frac{\sigma^2}{n} + \frac{\sigma^2}{n}\right) \\ &= \frac{1}{4}\left(\frac{4\sigma^2}{n}\right) = \frac{\sigma^2}{n}\end{aligned}$$

where σ^2 is the variance of the individual observation (y). Thus, two standard deviation (corresponding to 95%) error limits on any effect would be $\pm 2\sigma/\sqrt{n}$. The variance of the change in mean is

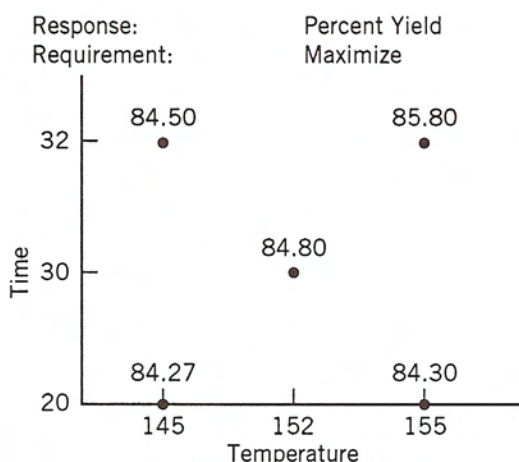
$$\begin{aligned}\text{Var}(\text{CIM}) &= \text{Var}\left[\frac{1}{5}(\bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5 - 4\bar{y}_1)\right] \\ &= \frac{1}{25}\left(\frac{4\sigma^2}{n} + \frac{16\sigma^2}{n}\right) = \left(\frac{20}{25}\right)\frac{\sigma^2}{n}\end{aligned}$$

Thus, two standard deviation error limits on the CIM are

$$\pm(2\sqrt{20/25})\sigma/\sqrt{n} = \pm 1.78\sigma/\sqrt{n}.$$

In the worksheet, σ is replaced by its estimate s .

The standard deviation σ is estimated by the range method. Let $y_i(n)$ denote the observation at the i th design point in cycle n and $\bar{y}_i(n)$ denote the corresponding average of $y_i(j)$, after cycle n ($j = 1, 2, \dots, n$). The quantities in row (iv) of the EVOP worksheet are the differences $y_i(n) - \bar{y}_i(n-1)$. The



Error Limits for Averages: ± 1.27			
Effects with	Temperature	2.75	± 1.27
95% error	Time	0.75	± 1.27
Limits:	Interaction	0.25	± 1.27
	Change in mean	0.50	± 1.13
Standard deviation:	0.90		

Figure 13.2 EVOP information board-cycle 1.

variance of these differences is

$$\text{Var}[y_i(n) - \bar{y}_i(n-1)] \equiv \sigma_D^2 = \sigma^2 \left(1 + \frac{1}{n-1} \right) = \sigma^2 \frac{n}{n-1}$$

The range of the differences, say R_D , is related to the estimate of the standard deviation of the differences by $\sigma_D = R_D/d_2$. The factor d_2 (which is widely used in quality control work) depends on the number of observations used in computing R_D . Now $R_D/d_2 = \sigma\sqrt{n/(n-1)}$, so

$$\hat{\sigma} = \sqrt{\frac{n-1}{n}} \frac{R_D}{d_2} = f_{k,n} R_D = s$$

can be used to estimate the standard deviation of the observations, where k denotes the number of points used in the design. For a 2^2 design with one center point we have $k = 5$, and for a 2^3 design with one center point we have $k = 9$. Values of $f_{k,n}$ are given in Table 13.3.

13.3 EVOP USING COMPUTER SOFTWARE

As originally proposed, EVOP was implemented with manual calculations using a worksheet format, as illustrated in the previous section. A more modern approach would be to implement EVOP using the computer. Spreadsheet software could be easily developed for this purpose. Alternatively, one could use any software program for the analysis of 2^k factorial designs to implement EVOP. To illustrate, we will show how the popular

DESIGN - EASE ANALYSIS				
Response: yield; File = No File			Run on 03/27/94 at 14:15:10	
Var	VARIABLE	Units	-1 LEVEL	+1 LEVEL
A	temp	degC	145.000	155.000
B	time	min	28.000	32.000
		COEFFICIENT	STANDARDIZED EFFECT	SUM OF SQUARES
OVERALL AVERAGE		73.6000		
	A	1.0000	2.0000	4.000000
	B	0.0000	0.0000	0.000000
	AB	0.5000	1.0000	1.000000
CENTER POINT		0.5000		0.200000

Computations done for Factorial

Model selected for Factorial:

Results of Factorial Model Fitting

ANOVA for Selected Model					
SOURCE	SUM OF SQUARES	DF	MEAN SQUARE	F VALUE	PROB > F
MODEL	5.000000	3	1.666667		
CURVATURE	0.200000	1	0.200000		
RESIDUAL	0.000000	0			
COR TOTAL	5.200000	4			
ROOT MSE			R-SQUARED 1.0000		
DEP MEAN			73.600000		

Final Equation in Terms of Uncoded Variables:

$$\begin{aligned}
 \text{yield} = & 268.500000 \\
 & - 1.300000 * \text{temp} \\
 & - 7.500000 * \text{time} \\
 & + 0.050000 * \text{temp} * \text{time}
 \end{aligned}$$

Figure 13.3 Design-Ease output after $n = 1$ cycles.

microcomputer program *Design-Ease* can be used to perform the EVOP calculations using the two cycles of data from the example in Section 13.2.

Figure 13.3 shows the output from *Design-Ease* after the end of the first EVOP cycle. Notice that the effects estimates for the main effects of temperature and time and the interaction effect estimates agree with those given in the EVOP worksheet Table 13.1. However, the CIM effect does not agree with the center point effect. The center point coefficient in Figure 13.3 is calculated as

$$\begin{aligned}\text{center point effect} &= \bar{y}_1 - \frac{1}{4}(\bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5) \\ &= 74 - \frac{1}{4}(73 + 74 + 75 + 72) \\ &= 74 - 73.5 \\ &= 0.5\end{aligned}$$

while the CIM is

$$\begin{aligned}\text{CIM} &= \frac{1}{5}(\bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5 - 4\bar{y}_1) \\ &= \frac{1}{5}[73 + 74 + 75 + 72 - 4(74)] \\ &= \frac{1}{5}(294 - 296) \\ &= -0.4\end{aligned}$$

However, it is obvious that both quantities provide an estimate of curvature in the true response function. Figure 13.4 is a square plot of the data from *Design-Ease* at the end of the first cycle.

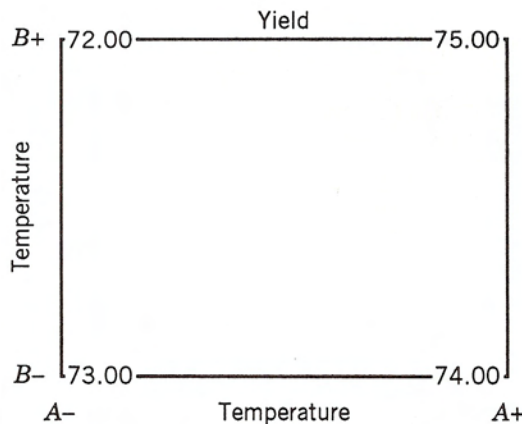


Figure 13.4 A square plot of the data from cycle 1 (from *Design-Ease*).

Response: yield; File = No File Run on 03/27/94 at 14:20:07

Var	VARIABLE	Units	-1 LEVEL	+1 LEVEL
A	temp	degC	145.000	155.000
B	time	min	28.000	32.000

VARIABLE	COEFFICIENT	STANDARDIZED EFFECT	SUM OF SQUARES
OVERALL AVERAGE	73.5000		
A	1.3750	2.7500	15.12500
B	0.3750	0.7500	1.12500
AB	0.1250	0.2500	0.12500
CENTER POINT	-0.6250		0.62500

Computations done for Factorial

Model selected for Factorial:

Results of Factorial Model Fitting

ANOVA for Selected Model

SOURCE	SUM OF SQUARES	DF	MEAN SQUARE	F VALUE	PROB > F
MODEL	16.37500	3	5.45833	4.962	0.0585
CURVATURE	0.62500	1	0.62500	0.5682	0.4849
RESIDUAL	5.50000	5	1.10000		
PURE ERROR	5.50000	5	1.10000		
COR TOTAL	22.50000	9			
ROOT MSE	1.048809		R-SQUARED	0.7486	
DEP MEAN	73.500000		ADJ R-SQUARED	0.5977	
C.V.	1.43%				

Predicted Residual Sum of Squares (PRESS) = 22.00000

VARIABLE	COEFFICIENT ESTIMATE	DF	STANDARD ERROR	t FOR HO COEFFICIENT=0	PROB> t
INTERCEPT	73.625000	1	0.370810		
A	1.375000	1	0.370810	3.708	0.0139
B	0.375000	1	0.370810	1.011	0.3583
AB	0.125000	1	0.370810	0.3371	0.7497
CENTER POINT	-0.625000	1	0.829156	-0.7538	0.4849

Figure 13.5 Design-ease output after $n = 2$ cycles.

Final Equation in Terms of Coded Variables:

$$\begin{aligned} \text{yield} = & 73.500000 \\ & + 1.375000 * A \\ & + 0.375000 * B \\ & + 0.125000 * A * B \end{aligned}$$

Final Equation in Terms of Uncoded Variables:

$$\begin{aligned} \text{yield} = & 83.000000 \\ & - 0.100000 * \text{temp} \\ & - 1.687500 * \text{time} \\ & + 0.012500 * \text{temp} * \text{time} \end{aligned}$$

Obs Ord	ACTUAL VALUE	PREDICTED VALUE	RESIDUAL	STUDENT LEVER	COOK'S RESID	DIST	t VALUE	RUN Ord
1	73.0000	72.0000	1.0000	0.500	1.348	0.364	1.512	3
2	71.0000	72.0000	-1.0000	0.500	-1.348	0.364	-1.512	2
3	74.0000	74.5000	-0.5000	0.500	-0.674	0.091	-0.632	8
4	75.0000	74.5000	0.5000	0.500	0.674	0.091	0.632	7
5	72.0000	72.5000	-0.5000	0.500	-0.674	0.091	-0.632	4
6	73.0000	72.5000	0.5000	0.500	0.674	0.091	0.632	10
7	75.0000	75.5000	-0.5000	0.500	-0.674	0.091	-0.632	6
8	76.0000	75.5000	0.5000	0.500	0.674	0.091	0.632	1
9	74.0000	73.0000	1.0000	0.500	1.348	0.364	1.512	9
10	72.0000	73.0000	-1.0000	0.500	-1.348	0.364	-1.512	5

Figure 13.5 (Continued).

Figure 13.5 presents the output from *Design-Ease* after the completion of the second cycle. The factorial effect estimates agree with those obtained from the tabular worksheet version of EVOP in Table 13.2. However, as noted previously, the test for curvature is performed as in a standard 2^2 factorial design with center points. In the analysis of variance portion of Figure 13.5 there is a formal statistical test for curvature (the P -value is 0.4849, so there is no indication of curvature). Also this computer program uses a t -statistic to test the significance of main effects and interactions, whereas the tabular EVOP essentially uses confidence intervals. We observe that the main effect of factor A = temperature is significant (the P -value for the t -test is 0.0139), so the conclusions from this analysis would agree with those from the tabular EVOP; that is, the temperature variable should be adjusted in the positive direction.

The computer software uses the error mean square from the analysis of variance to estimate σ^2 . The process standard deviation is estimated as the square root of this quantity, or $\hat{\sigma} = \sqrt{MS_E} = \sqrt{5.5} = 1.049$. This estimate is

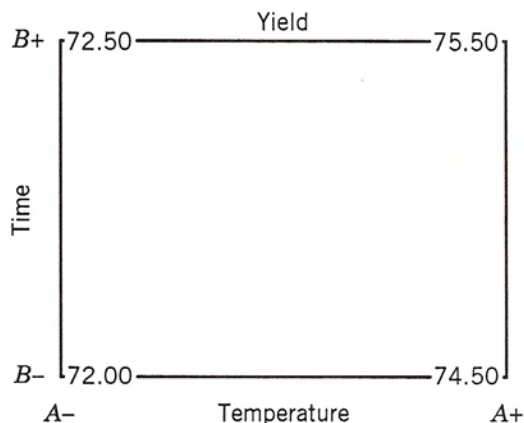


Figure 13.6 A square plot of the data after cycle $n = 2$ (from Design-Ease).

slightly different than the error estimate obtained in the tabular EVOP ($s = 0.90$). However, the tabular EVOP procedure estimates σ using a range method, and we would generally prefer the analysis of variance approach. Figure 13.6 shows the square plot of average responses at the end of the second cycle.

13.4 SIMPLEX EVOP

The experimental design usually employed in EVOP is a 2^k factorial augmented by a center point. An alternative EVOP procedure has been suggested by Spendley et al. (1962). Their scheme is based on the *simplex*, which we recall from Chapter 6 is an orthogonal first-order experimental design, requiring only one more observation than the number of variables under investigation. Thus, if k variables are being studied, then the number of trials in the design $n = k + 1$. The n observations are taken at the vertices of a regular-sided simplex, which for $k = 2$ is an equilateral triangle and for $k = 3$ is a tetrahedron. The design matrix $\mathbf{D}$ for a simplex of arbitrary orientation may be constructed from the last k column of $n^{1/2}\mathbf{O}$, where $\mathbf{O}$ is any $(n \times n)$ orthogonal matrix having elements in the first column equal. The design points are the rows of the $\mathbf{D}$ matrix. The j th row of $\mathbf{D}$ will be denoted vectorially by $\mathbf{d}_j'$. The advantage of this design relative to a factorial is that fewer trials are required.

To apply this technique in a two-factor or a three-factor EVOP would require three and four periods, respectively, to observe the process response (yield, say) at the design points. Then the simplex EVOP procedure would adjust the process variables according to the following rules (assuming that the objective is to maximize the response).

1. Denote by y_i the response at the i th design point, $i = 1, 2, \dots, n$. Let the minimum value of the response occur at design point $\mathbf{d}'_j$. Form a new simplex by deleting $\mathbf{d}'_j$ from $\mathbf{D}$ and substituting the new design point,

$$\mathbf{d}'_j^* = 2n^{-1}(\mathbf{d}'_1 + \mathbf{d}'_2 + \dots + \mathbf{d}'_{j-1} + \mathbf{d}'_{j+1} + \dots + \mathbf{d}'_n) - \mathbf{d}'_j \quad (13.1)$$

Run the process for the next period using the factor levels for $x_1, x_2, \dots, x_n$ that are the elements of $\mathbf{d}'_j^*$.

2. Apply rule 1 unless a design point has occurred in n successive simplexes without being eliminated. Should this situation arise for the i th design point, discard y_i and run the process during the next period using the factor levels in $\mathbf{d}'_i$. Then apply rule 1.
3. Should y_i be the minimum response in the m th simplex and y_{i^*} be the minimum yield in the $(m+1)$ th simplex, do not return to the m th design. Instead of oscillating, move from the $(m+1)$ th design by discarding the second largest absolute current error.

We have described these rules for the case of maximizing the response. To minimize the response, replace the work "minimum" with "maximum" in the above rules.

Figure 13.7 shows how a simplex EVOP scheme can systematically move a process from a relative poor starting point to a much improved estimate of the optimum. We note also that the simplex can be used effectively in some

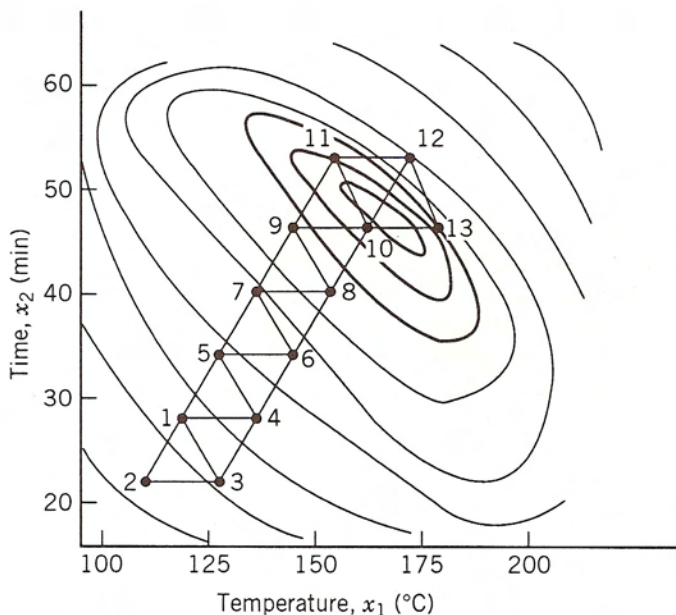


Figure 13.7 A simplex EVOP scheme for $k = 2$ variables.

situations as a type of "automatic" steepest ascent procedure. It has also been used as a mathematical optimization algorithm.

While some authors have advocated the sequential use of the simplex as a replacement for the more conventional factorial-based EVOP (indeed, some have suggested using the simplex as a replacement for variable screening and steepest ascent), we are not generally in favor of this. The simplex design does not provide direct information about interaction effects. In fact, because the simplex is a resolution III design, main effects and two-factor interactions are aliased. Thus the design may not provide information useful in building up process knowledge. Furthermore, when there is a moderate level of noise (error) associated with the response, then the sequential simplex may behave erratically. Replicate runs could be made at each vertex to counteract the effect of noise, but this increases the resources required to run the simplex, and its potential advantage in this regard to conventional factorials would be diminished.

13.5 SOME PRACTICAL ADVICE ABOUT USING EVOP

Our experience in using EVOP has led to several observations and suggestions about its practical implementation that may prove helpful. In this section, we share some of these ideas.

Usually, some care needs to be taken to ensure that a reasonable list of candidate variables are available for EVOP analysis and experimentation. We recommend starting with two (or perhaps three) variables that operating personnel think are the most important, but if several cycles occur (say five to eight, or so) and no significant effects emerge, then new variables should be introduced into the design (or new levels of the old variables tried) and a new EVOP phase started. It is particularly important to keep an open mind when identifying candidate variables. Often we have found that a variable was not realized to be important simply because it had never been changed.

Sometimes a process experiences relative large run-to-run variation, and this is used as an "excuse" for not using EVOP (or any statistically designed experiments, for that matter). This is certainly not a valid argument, because each cycle of the EVOP design is a replicate, and replication is a very effective noise-reduction technique. By building up information over several cycles and working with effect estimates that are based on averages of the responses at each design point, quite often large and important effects can be discovered even in noisy processes. It is also possible to discover that some variable settings result in less variability than do others (indeed, you could use the range or standard deviation of the observation at each design point as a second response). In noisy processes, sometimes more cycles may be required for the important effects to emerge, but the presence of process variability is not a deterrent to the use of designed experiments—it's the reason that statistically based designs *must* be used.

We have encountered some objection to the use of EVOP on the grounds that it is in violation of some of the principles of statistical process control

(SPC). Specifically, SPC encourages operating personnel to leave the process alone so long as it is "statistical control," and this is directly opposed to the EVOP procedure which introduces changes in some process variables almost continuously. We must remember that the objectives of these two procedures are different. EVOP is concerned with optimization, including following a process that drifts over time. SPC, on the other hand, is concerned with the detection and elimination of isolatable, external upsets in the process (called *assignable causes*) that may increase process variability or shift the process off-target. It may not be desirable to monitor and tightly control the process around the wrong target. Furthermore, the process knowledge generated through any designed experiment may lead to improvements in operating performance far faster and more efficiently than the use of SPC methods alone.

Finally, we give a few remarks on training and education in EVOP methods. We recommend that education concerning EVOP be included as part of a basic course in experimental design fundamentals. This course should be offered to process engineers, quality engineers, development personnel, researchers, and other technical professionals. We have conducted courses such as this for many years. Usually they are from 3 to 5 days in length. Shorter versions of this course (1–2 days) should be given to key management personnel, so that they will understand the basic notions of designed experiments as well as the EVOP strategy. Plant operating personnel can usually be trained to run and evaluate EVOP schemes in about one-half day. We have found that training and education are critical to the successful implementation of both EVOP (in particular), and experimental design methods (in general).