## D-Optimality For Designs With Different Numbers of Runs

by
Walter T. Federer

BU-948-M *
December, 1987


#### Abstract

A per-run measure of D-optimality is given for designs with unequal numbers of runs. The measure is illustrated with examples. Although the number of runs may vary with the design, the parameter set should be similar and perhaps the same for all designs being considered. Some comments are made relative to this and illustrated with examples.


## INTRODUCTION

Situations arise wherein an investigator desires to determine the relative merits of a group of treatment designs which have different numbers of runs. For example, several fractional replicates may be under consideration for a particular investigation. If one uses D-optimality, i.e., the determinant of $X$ 'X where $X$ is the design matrix for a single-degree-of-freedom set of parameters, the design with the larger number, $r$, of runs, may turn out to have the larger value simply because there are more runs. In order to offset this and to take account of the number of runs it is suggested that the following per-run D-optimality measure could be used:

$$
\left|X^{\prime} X\right| / r=D_{r}
$$

where $|$.$| is the value of the determinant.$

[^0]The above measure may be criticized on the ground that it does not take into account the increase in every diagonal element of $X$ ' $X$ when more runs are included. To take account of this, it is suggested that D-optimality for fractions with different numbers of runs be measured by

$$
\left|\frac{1}{r} X^{\prime} X\right|=D_{r m}
$$

This corresponds to using variances and covariances rather than sums of squares and cross products. Such a measure as this appears to overcompensate and hence is not used here.

Some examples illustrating these measures are presented below. Also, the selection of a relevant set of parameters as the estimable parameter set is a problem. It is noted that this set may vary from fraction to fraction.

## EXAMPLE 1

Let design 1 be the fractional replicate for $x=9$ runs obtained from a latin square of order 3. The design is:


The corresponding contrast design matrix $X$, parameter vector $\beta$ and observation vector $Y$ is

$$
X \boldsymbol{X}=\left[\begin{array}{rrrrrrrrr}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 0 & -2 & -1 & 1 & 0 & -2 \\
1 & 1 & 1 & -1 & 1 & 0 & -2 & -1 & 1 \\
1 & 0 & -2 & 1 & 1 & 0 & -2 & 0 & -2 \\
1 & 0 & -2 & 0 & -2 & 1 & 1 & -1 & 1 \\
1 & 0 & -2 & -1 & 1 & -1 & 1 & 1 & 1 \\
1 & -1 & 1 & 1 & 1 & -1 & 1 & -1 & 1 \\
1 & -1 & 1 & 0 & -2 & 0 & -2 & 1 & 1 \\
1 & -1 & 1 & -1 & 1 & 1 & 1 & 0 & -2
\end{array}\right]\left[\begin{array}{l}
M \\
A_{1} \\
A_{2} \\
B_{1} \\
B_{2} \\
C_{1} \\
C_{2} \\
D_{1} \\
D_{1}
\end{array}\right]=E\left[\begin{array}{l}
Y_{0000} \\
Y_{0121} \\
Y_{0212} \\
Y_{1011} \\
Y_{1102} \\
Y_{1220} \\
Y_{2022} \\
Y_{2110} \\
Y_{2201}
\end{array}\right]=E(Y)
$$

where $E[\cdot]$ denotes expectation.

The determinant of $X$ ' $X$ is

$$
\left|X^{\prime} X\right|=\left[\begin{array}{rrrrrrrrr}
9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 18 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 6 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 18 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 6 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 18 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 6 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 18
\end{array}\right]=9 \cdot 6^{4} \cdot 18^{4}=1,224,440,064
$$

Since there were $r=9$ runs,

$$
D_{9}=\left|X^{\prime} X\right| /_{9}=9 \cdot 6^{4} \cdot 18^{4} / 9=6^{4} \cdot 18^{4} .
$$

The aliasing structure and degrees of freedom for the above fractional replicate is:

Effect

$$
M \approx A B^{2} C
$$

$\mathrm{A} \approx \mathrm{BC}^{2}+\mathrm{ABC}^{2}$
$\mathrm{B} \approx \mathrm{AC}+\mathrm{ABC}$
$\mathrm{C} \approx \mathrm{AB}^{2}+\mathrm{AB}^{2} \mathrm{C}^{2}$
$A B \approx A C^{2}+B C$

## Degrees of Freedom

1

2

2

2

2
where $\approx$ means confounded with and the effects are geometrical components (see e.g., Federer, 1955). The estimable parameter set is $M, A_{1}, B_{1}, C_{1}$, $A_{2}, B_{2}, C_{2}$ and contrasts among the levels of the geometrical component of interaction AB .

EXAMPLE 2
A competing design for three factors at three levels would be a response surface design with 4 center points and $2^{3}$ corner points. $X B=E(Y)$ would be

$$
\left[\begin{array}{rrrrrrrrr}
1 & 1 & 1 & 1 & -1 & 1 & -1 & -1 & -1 \\
1 & 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & -1 & 1 & -1 & 1 & -1 & -1 \\
1 & -1 & 1 & 1 & -1 & -1 & 1 & -1 & 1 \\
1 & -1 & 1 & -1 & -1 & 1 & 1 & 1 & -1 \\
1 & -1 & 1 & 1 & 1 & -1 & -1 & 1 & -1 \\
1 & -1 & 1 & -1 & 1 & 1 & -1 & -1 & 1 \\
1 & 0 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -2 & 0 & 0 & 0 & 0 & 0 & 0
\end{array}\right]\left[\begin{array}{l}
M_{1} \\
A_{1} \\
A_{2} \\
B_{1} \\
C_{1} \\
A_{1} B_{1} \\
A_{1} C_{1} \\
B_{1} C_{1} \\
A_{1} B_{1} C_{1}
\end{array}\right]=E\left[\begin{array}{l}
Y_{002} \\
Y_{022} \\
Y_{000} \\
Y_{020} \\
Y_{202} \\
Y_{222} \\
Y_{200} \\
Y_{220} \\
Y_{111} \\
Y_{111} \\
Y_{111} \\
Y_{111}
\end{array}\right]
$$

Note that the contrasts are different than for design 1 and that $A_{2}, B_{2}$, and $C_{2}$ are completely confounded with each other, which is the reason for omitting $B_{2}$ and $C_{2}$ in the parameter vector $\beta$.

An estimable parameter set is $M, A_{1}, A_{2}, B_{1}, C_{1}, A_{1} B_{1}, A_{1} C_{1}, B_{1} C_{1}$, and $A_{1} B_{1} C_{1}$. The absolute value of the determinant of $X^{\prime} X$ is:

$$
\left[\begin{array}{rrrrrrrrr}
12 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 24 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 8 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 8 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 8 & 0 & 0 & 0 \\
0 & 0 & 0 & 8 & 0 & 0 & 8 & 0 & 0 \\
0 & 0 & 0 & 0 & 8 & 0 & 0 & 8 & 0 \\
0 & 0 & 0 & 0 & 0 & 8 & 0 & 0 & 8
\end{array}\right]=12(24)\left(8^{7}\right)=603,979,776
$$

The aliasing structure in terms of the geometrical effects is rather complex. For the aliasing structure in terms of contrasts as given in $\beta$ above, the aliasing structure may be obtained as follows. Let $X_{27}$ be the contrast matrix for a $3^{3}$ factorial. Partition $X_{27}$ as

$$
x_{27}=\left[\begin{array}{cc}
x_{9 \times 9} & x_{9 \times 18} \\
x_{18 \times 9} & x_{18 \times 8}
\end{array}\right]
$$

where $X_{9 \times 9}$ is the first nine rows of the above $X$ matrix which is the design matrix for the vector of means for the nine distinct treatments. Then, $X_{9 \times 9} \beta+X_{9 \times 18} \beta_{0}=E(Y)$ where $\beta_{0}$ is the parameter vector for the remaining contrasts from a $3^{3}$ factorial not included in $B$ above. Then

$$
\beta+\left(X_{9 \times 9}^{\prime} X_{9 \times 9}\right)^{-1} X_{9 \times 9}^{\prime} X_{9 \times 18} \beta_{0}=\beta+A \beta_{0}=\left(X_{9 \times 9}^{\prime} X_{9 \times 9}\right)^{-1} X_{9 \times 9}^{\prime} E(Y)
$$

where A denotes the aliasing structure of other effects with those in $\beta$.

## EXAMPLE 3

Consider the design given in Table 8A. 8 in Cochran and Cox (1957) for $k=3$ factors $A, B$, and $C$. The contrast matrix $X$, the parameter set vector $B$, and the vector of observations $Y$ are:
$X \boldsymbol{B}=\left[\begin{array}{rrrrrrrrrrrr} \\ 1 & -1 & -1 & -1 & 1 & 1 & 1 & -1 & c & c & c & c^{2} \\ 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 & c & c & c & c^{2} \\ 1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 & c & c & c & c^{2} \\ 1 & 1 & 1 & -1 & 1 & -1 & -1 & -1 & c & c & c & c^{2} \\ 1 & -1 & -1 & 1 & 1 & -1 & -1 & 1 & c & c & c & c^{2} \\ 1 & 1 & -1 & 1 & -1 & 1 & -1 & -1 & c & c & c & c^{2} \\ 1 & -1 & 1 & 1 & -1 & -1 & 1 & -1 & c & c & c & c^{2} \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & c & c & c & c^{2} \\ 1 & a & 0 & 0 & 0 & 0 & 0 & 0 & e & d & d & d e \\ 1 & -a & 0 & 0 & 0 & 0 & 0 & 0 & e & d & d & d \\ 1 & 0 & a & 0 & 0 & 0 & 0 & 0 & d & e & d & d e \\ 1 & 0 & -a & 0 & 0 & 0 & 0 & 0 & d & e & d & d e \\ 1 & 0 & 0 & a & 0 & 0 & 0 & 0 & d & d & e & d^{2} \\ 1 & 0 & 0 & -a & 0 & 0 & 0 & 0 & d & d & e & d^{2} \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & d & d & d & d^{2} \\ A_{1} \\ B_{1} \\ C_{1} \\ A_{1} B_{1} \\ A_{1} C_{1} \\ B_{1} C_{1} \\ A_{1} B_{1} C_{1} \\ A_{2} \\ B_{2} \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & d & d \\ B_{2} \\ C_{2} \\ A_{2} B_{2}\end{array}\right]=\left[\begin{array}{l}Y_{000} \\ Y_{200} \\ Y_{020} \\ Y_{220} \\ Y_{002} \\ Y_{2} \\ 1\end{array}\right.$

Note that the mean of the last column needs to be subtracted from each element of that column to form a contrast set. In the above $a=2.75 \cong$ $.6818, c=.3172, d=-.6828, e=2.1456, \mathrm{de}=-1.4651, \mathrm{~d}^{2}=.4663$, and $c^{2}=.1006$.

The parameters $A_{2} C_{2}, B_{2} C_{2}$, and $A_{2} B_{2} C_{2}$ are not estimable parameters together with the above set. Since there are 15 distinct combinations, three additional parameters are estimable. These were not determined but could be if desired.

For the above,
$\left|X^{\prime} X\right|=\left[\begin{array}{cccccccccccc}20 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & b & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & b & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 8 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 8 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 8 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & f & g & g & h \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & g & f & g & h \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & g & g & f & h \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & h & h & h & i\end{array}\right]=20 b^{3} 8^{4}(2.0850)(12.9321)(15.9997)(23.4126)$,
where $b=8+2^{2.5} \cong 13.6569, f=14.6743, g=-1.3254, h=-6.5781$, and $i=$ 10.4065. The determinant of $X^{\prime} X$ omitting $A_{1} B_{1} C_{1}$ and $A_{2} B_{2}$ is $20(13.6569)^{3} 8^{3}(3,077.9006)=2,608,292,814(3077.9006)$.

Since there are 15 distinct combinations, there are 15 parameters in B. There are $r=20$ runs. The sum of squares among the six responses $Y_{111}$ provides an error for testing effects. A usual way for partitioning degrees of freedom among the 20 observations is:

Total 20
Correction for mean 1
First order efects ( $A_{1}, B_{1}, C_{1}$ )
Second order effects ( $A_{2}, B_{2}, C_{2}, A_{1} B_{1}, A_{1} C_{1}, B_{1} C_{1}$ )
Lack of fit (remaining parameters)
Error

Note that designs can be compared on the basis of the set of parameters in $\beta$, the determinants of $X^{\prime} X$, and/or other criteria (see e.g., Raktoe et al., 1981, Chapter 5). The usual situation in regard to D-optimality is that $B$ is implicitly assumed to be fixed and the same for all the designs in the class being compared. For response surface situations, the restrictions are not so rigid regarding $\beta$. Here may be partitioned into first order parameters, second order parameters, and lack of fit parameters. The first two are clearly defined but the last is not. Lack of fit parameters for the $B$ in Example 1 are $A B \cong A C^{2} \cong B C$ while for Example 3 , they are $A_{1} B_{1} C_{1}, A_{2} B_{2}$, and three other parameters. In Example 2, the lack of fit parameter is $A_{1} B_{1} C_{1}$ and the second order parameters are $A_{2}, A_{1} B_{1}, A_{1} C_{1}$, and $B_{1} C_{1} ; A_{2}$ is completely confounded with $B_{2}$ and $C_{2}$ which may not be a problem if $A_{2}, B_{2}$ and $C_{2}$ all respond in the same direction.

Despite the above, an investigator might be interested in the design in Example 1 plus the fold-over fraction (see Raktoe and Federer, 1986), with $r=18$ runs versus the design of Example 3 with $r=20$ runs. Then for whatever set of parameters under consideration the $X$ ' $X$ matrices are determined for each design. Then, to compare the relative efficiencies of the two designs, one takes the determinants of $X^{\prime} X$ for each design and divides by the number of runs; then, the ratio of these two values, i.e., $\mathrm{D}_{18} / \mathrm{D}_{20}$ is one measure of the relative efficiencies of the two designs. A fold-over design for the design in Example 1 is:

| Design of Example 1 | Fold-Over Design |
| :---: | :---: |
|  | 222 |
| 012 | 210 |
| 021 | 201 |
| 101 | 121 |
| 110 | 112 |
| 122 | 100 |
| 202 | 020 |
| 211 | 011 |
| 220 | 002 |

For the above $2 / 3 r d s$ fraction of a $3^{3}$, the main effects are not confounded with two-factor interaction effects. For the parameter vector $B^{\prime}=\left[M, A_{1}, B_{1}, C_{1}, A_{2}, B_{2}, C_{2}, A_{1} B_{1}, A_{1} C_{1}, B_{1} C_{1}\right]$, the design matrix $X$ is

$$
\left[\begin{array}{rrrrrrrrrr}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 0 & -2 & -1 & 1 & 0 & -1 & 0 \\
1 & 1 & 1 & -1 & 1 & 0 & -2 & -1 & 0 & 0 \\
1 & 0 & -2 & 1 & 1 & 0 & -2 & 0 & 0 & 0 \\
1 & 0 & -2 & 0 & -2 & 1 & 1 & 0 & 0 & 0 \\
1 & 0 & -2 & -1 & 1 & -1 & 1 & 0 & 0 & 1 \\
1 & -1 & 1 & 1 & 1 & -1 & 1 & -1 & 1 & -1 \\
1 & -1 & 1 & 0 & -2 & 0 & -2 & 0 & 0 & 0 \\
1 & -1 & 1 & -1 & 1 & 1 & 1 & 1 & -1 & -1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & 1 & 1 & 1 \\
1 & -1 & 1 & 0 & -2 & 1 & 1 & 0 & -1 & 0 \\
1 & -1 & 1 & 1 & 1 & 0 & -2 & -1 & 0 & 0 \\
1 & 0 & -2 & -1 & 1 & 0 & -2 & 0 & 0 & 0 \\
1 & 0 & -2 & 0 & -2 & -1 & 1 & 0 & 0 & 0 \\
1 & 0 & -2 & 1 & 1 & 1 & 1 & 0 & 0 & 1 \\
1 & 1 & 1 & -1 & 1 & 1 & 1 & -1 & 1 & -1 \\
1 & 1 & 1 & 0 & -2 & 0 & -2 & 0 & 0 & 0 \\
1 & 1 & 1 & 1 & 1 & -1 & 1 & 1 & -1 & 1
\end{array}\right]\left[\begin{array}{l}
M_{0} \\
A_{1} \\
A_{2} \\
B_{1} \\
B_{1} \\
B_{2} \\
C_{1} \\
\mathrm{C}_{2} \\
\mathrm{~A}_{012} B_{1} \\
Y_{021} \\
Y_{101} \\
\mathrm{~A}_{1} C_{1} \\
\mathrm{~B}_{1} C_{1} \\
Y_{122} \\
Y_{202} \\
Y_{211} \\
Y_{220} \\
Y_{222} \\
Y_{210} \\
Y_{201} \\
Y_{121} \\
Y_{112} \\
Y_{100} \\
Y_{020} \\
Y_{011} \\
Y_{002}
\end{array}\right]=\left[\begin{array}{l} 
\\
Y_{0} \\
1
\end{array}\right]
$$

$$
\left|X^{\prime} X\right|=\left[\begin{array}{rrrrrrrrrr}
18 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 \\
0 & 12 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 \\
0 & 0 & 36 & 0 & 0 & 0 & 0 & 0 & 0 & -4 \\
0 & 0 & 0 & 12 & 0 & 0 & 0 & 0 & 0 & 2 \\
0 & 0 & 0 & 0 & 36 & 0 & 0 & 0 & 6 & 2 \\
0 & 0 & 0 & 0 & 0 & 12 & 0 & 0 & 0 & -2 \\
0 & 0 & 0 & 0 & 0 & 0 & 36 & 6 & 0 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 & 6 & 8 & -2 & 4 \\
0 & 0 & 0 & 0 & 6 & 0 & 0 & -2 & 8 & 0 \\
2 & 2 & -4 & 2 & 2 & -2 & 2 & 4 & 0 & 8
\end{array}\right]=268,469,821,440
$$

Then $\mathrm{D}_{18} / \mathrm{D}_{20}=(268,469,821,440 / 18) /(80,300,177,774.6 / 20)=3.34(20 / 18)=$ 3.7, indicating the design with 18 runs (denoted as Example 4) is nearly four times better using D-optimality as a criterion. Note that the parameter set for the two designs is the same.

Another way to compare the designs is as follows:

|  | Degrees of freedom for Example |  |  |  |
| :--- | :--- | ---: | ---: | ---: |
| Source of variation | 1 | 2 | 3 | 4 |
| Total | 9 | 12 | 20 | 18 |
| Correction for mean | 1 | 1 | 1 | 1 |
| First order effects | 3 | 3 | 3 | 3 |
| Second order effects | 3 | 4 | 6 | 6 |
| Lack of fit terms | 2 | 1 | 5 | 8 |
| Error among duplicates | 0 | 3 | 5 | 0 |

Note that some "lack of fit" effects may sometimes to be nonexistent and hence could be considered to be a measure of error variation.

## LITERATURE CITED

Cochran, W. G. and G. M. Cox (1957). Experimental Designs, 2nd edition, John Wiley and Sons, Inc., New York.

Federer, W. T. (1955). Experimental Design - Theory and Application, Macmillan, New York (republished by Oxford and IBH Publishing Co., New Delhi, 1968 and 1974).

Raktoe, B. L. and W. T. Federer (1968). A unified approach for constructing a useful class of non-orthogonal main effect plans in $k^{n}$ factorials, J. Royal Statistical Soc., Series $B, 30,371-380$

Raktoe, B. L., A. Hedayat, and W. T. Federer (1981). Factoríal Designs, John Wiley and Sons, Inc., New York.


[^0]:    * In the Technical Report Series of the Biometrics Unit, Cornell University, Ithaca, NY 14853, U.S.A.

