# A Note on Saturated First-Order Design with Foldover Structure 

DENNIS K. J. LIN ${ }^{1}$ AND LILI XIAO ${ }^{2}$<br>${ }^{1}$ Department of Statistics, Pennsylvania State University, University Park, Pennsylvania, USA<br>${ }^{2}$ Tsinghua University, Beijing, China

A first-order saturated design is the smallest design resulting in unbiased estimates for all main effects. It could be misleading in the presence of interaction effects. This article provides a simple class of first-order saturated designs in which specific two-factor interactions are orthogonal to many of the main effects, while keeping rather high design efficiencies.

Keywords: D-optimal design; Foldover; Interaction effects; Main effect; Saturated design.

## 1. Introduction

Consider the first-order model of $k$ variables in $n$ runs,

$$
\mathbf{y}=\beta_{0} \mathbf{1}+\beta_{1} \mathbf{x}_{\mathbf{1}}+\ldots+\beta_{k} \mathbf{x}_{\mathbf{k}}+\epsilon=X \beta+\epsilon,
$$

where $\mathbf{y}$ is an $n \times 1$ vector of observations, $\mathbf{1}$ is an $n \times 1$ vector whose entries are all ones, $\mathbf{x}_{\mathbf{i}}$ is an $n \times 1$ vector for the $i$ th factor, $\beta$ is the $(k+1) \times 1$ vector of coefficients to be estimated, and $\epsilon$ is the noise vector. When $n=k+1$, the design matrix $X$ is a $(k+1) \times$ $(k+1)$ square matrix. This is the smallest design possible to estimate all $\beta_{i}$ 's; such a design is called a saturated (first-order) design. This is especially popular when the experimental costs are high. Construction of saturated design has received a great deal of attention in the literature. One main concern for a saturated design is that its estimates for the $\beta_{i}$ 's may be misleading in the presence of two-factor interactions.

This article proposes a new class of saturated (first-order) design in which specific two-factor interactions are orthogonal to as many main effects. It can be shown that the proposed designs are as near efficient as the optimal (D-optimal, say) design, but main effects are orthogonal to some two-factor interactions. For simplicity of presentation, all proofs are given in Appendix A.

## 2. Proposed Design

Consider a two-level design matrix $X$ of the form

$$
X=\left(\begin{array}{rr}
X_{1} & X_{2} \\
X_{1} & -X_{2}
\end{array}\right)
$$

where $X_{1}$ is an $(n / 2) \times k_{1}$ matrix whose entries in the first column are all ones, $X_{2}$ is $(n / 2) \times$ $k_{2}$ matrix, and $k_{1}+k_{2}=n, n$ is even. Divide the factors into two groups A and B. Factors in Group A follow the design of $\binom{X_{1}}{X_{1}}$, while factors in Group B follow the design of $\binom{X_{2}}{-X_{2}}$. It is obvious that all factors in Group B keep the foldover property, namely, all main effects are orthogonal to their two-factor interactions (see, e.g., Li and Lin 2003). Furthermore, we have the following property.

## Property 1:

1. All main effects of $x_{i}$ and $x_{j}$ are orthogonal, for all $x_{i}$ in Group A and $x_{j}$ in Group B.
2. All two-factor interactions $x_{i} x_{j}$ are orthogonal to main effect $x_{k}$, for
(a) all $x_{i}$ and $x_{j}$ in Group A, and $x_{k}$ in Group B;
(b) all $x_{i}$ and $x_{j}$ in Group B, and $x_{k}$ in Group B;
(c) all $x_{i}$ in Group B, and $x_{j}$ and $x_{k}$ in Group A.

In short, all main effects in Group A are orthogonal to all main effects in Group B. If $X_{1}$ and $X_{2}$ are both orthogonal designs, $X$ will be an orthogonal design. All main effects in Group B are orthogonal to two-factor interactions within Group B and within Group A, while all main effects in Group A are orthogonal to all two factor interactions with one factor in Group A and the other in Group B. Such a design will be rather robust against potential interaction effects (a nice property by foldover), but with only half the run size required of a full foldover. It is thus desirable to have as many design columns in Group B as possible. Property 2 given next, however, indicates that the maximal number of columns possible in Group B is $k_{2}=n / 2$ for the design matrix to be nonsingular.

Property 2: If $X$ is full rank, then $k_{1}=k_{2}=n / 2$.
Without loss of generality, each design column is coded $\pm 1$ for high and low levels. Take D-optimality as an example, which maximizes the determinant of the $X^{\prime} X$ matrix, $\left\|X^{\prime} X\right\|$. Other optimalities can be used as well. It can be shown that:
Property 3: $\left\|X^{\prime} X\right\|=2^{n} \times\left\|X_{1}^{\prime} X_{1}\right\| \times\left\|X_{2}^{\prime} X_{2}\right\|$.
With Property 3 in mind, it is natural to employ D-optimal design of size $(n / 2)$ for both $X_{1}$ and $X_{2}$ matrices. These D -optimal saturated designs are available in the literature, especially for small $n$ (see, e.g., http://www.indiana edu/maxdet).

Take $n=6$ as an example; $n / 2$ is 3 and a D-optimal $3 \times 3$ saturated design is known to be

$$
X_{1}=X_{2}=\left(\begin{array}{rrr}
1 & -1 & -1 \\
1 & -1 & 1 \\
1 & 1 & -1
\end{array}\right) .
$$

Therefore, the proposed saturated design for five factors is

$$
X=\left(\begin{array}{cc}
X_{1} & X_{2} \\
X_{1} & -X_{2}
\end{array}\right)=\left(\begin{array}{rrrrrr}
I & x_{1} & x_{2} & x_{3} & x_{4} & x_{5} \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & 1 & 1 & -1 & 1 \\
1 & 1 & -1 & 1 & 1 & -1 \\
1 & -1 & -1 & -1 & 1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 \\
1 & 1 & -1 & -1 & -1 & 1
\end{array}\right)
$$

The design matrix has the following properties:

1. Main effects of factors $x_{1}, x_{2}$ are orthogonal to main effects of factors $x_{3}, x_{4}, x_{5}$.
2. Main effects of factors $x_{1}, x_{2}$ are orthogonal to two-factor interactions of $x_{1} x_{3}, x_{1} x_{4}, x_{1} x_{5}$, $x_{2} x_{3}, x_{2} x_{4}, x_{2} x_{5}$.
3. Main effects of factors $x_{3}, x_{4}, x_{5}$ are orthogonal to two-factor interactions of $x_{1} x_{2}, x_{3} x_{4}$, $x_{3} x_{5}, x_{4} x_{5}$.
4. $\left\|X^{\prime} X\right\|=2^{14}$.

If a $6 \times 6 \mathrm{D}$-optimal design is used, its determinant is $\left\|X^{\prime} X\right\|=5^{2} \times 2^{10}$. In terms of d-efficiency (as explained later) the proposed design has $92.8 \%$ d-efficiency. However, none of main effects for the D-optimal design are orthogonal to any two-factor interactions (except the trivial cases that interaction $x_{i} x_{j}$ is always orthogonal to main effects $x_{i}$ and $x_{j}$ ).

Table 1 displays the comparisons of d-efficiencies between the $n \times n$ D-optimal designs and the proposed saturated designs, for $2 \leq n \leq 60$. Define (see, e.g., Lin 1993) d-efficiency $=\left\|X^{\prime} X\right\|^{1 / n} / n$, and the relative ratio RR is defined as

$$
R R=\frac{\mathrm{d}-\operatorname{eff}_{P}}{\mathrm{~d}-\operatorname{eff}_{D}}
$$

where d-eff $P_{P}$ and d-eff ${ }_{D}$ are the d-efficiencies for the proposed design and the D-optimal design, respectively.

From Table 1, it is obvious that the loss of d-efficiency is rather limited-the relative ratio is between $90.5 \%$ and $100 \%$. However, the proposed design is robust to many (although not all) interaction effects. The same observation can be made for larger designs. Comparisons for $62 \leq n \leq 120$ are given in Appendix B. It is interesting to note that the proposed design for $n=94$ results in a higher d-efficiency than the published D-optimal design (see, e.g., Koukouvinos et al. 2000).

To use these newly proposed designs in practice, the experimenter should group all factors into two groups, such that potential two-factor interactions only occur within each group, but not between groups. Then assign sensitive factors to Group B.

## 3. Final Remarks

As pointed out by one referee, "Clearly for any saturated first-order design every 2-factor interaction must be confounded (partially or completely) with at least one main effect." With foldover structure, the proposed designs allows some specific two-factor interactions to be orthogonal to as many main effects as possible. The general property is described in Property 1 for practical uses.

Table 1
Comparisons of d-efficiencies between D-optimal design and the proposed design

| $n$ | d-eff $_{D}(\%)$ | d-eff $_{P}(\%)$ | $\mathrm{RR}(\%)^{*}$ | $n$ | d-eff $_{D}(\%)$ | d-eff $_{P}(\%)$ | $\mathrm{RR}(\%)^{*}$ |
| ---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2 | 100 | 100 | 100 | 32 | 100 | 100 | 100 |
| 4 | 100 | 100 | 100 | 34 | $98.0^{\dagger}$ | 96.6 | 98.6 |
| 6 | 90.5 | 84.0 | 92.8 | 36 | 100 | 96.7 | 96.7 |
| 8 | 100 | 100 | 100 | 38 | 98.4 | 95.4 | 97.0 |
| 10 | 94.1 | 94.1 | 100 | 40 | 100 | 100 | 100 |
| 12 | 100 | 90.5 | 90.5 | 42 | 98.6 | 97.6 | 99.0 |
| 14 | 95.7 | 87.8 | 91.7 | 44 | 100 | 96.8 | 96.8 |
| 16 | 100 | 100 | 100 | 46 | 98.7 | 95.8 | 97.1 |
| 18 | 96.7 | 93.2 | 96.4 | 48 | 100 | 100 | 100 |
| 20 | 100 | 94.1 | 94.1 | 50 | 98.8 | 98.8 | 100 |
| 22 | $96.8^{\dagger}$ | 91.5 | 94.5 | 52 | 100 | 97.7 | 97.7 |
| 24 | 100 | 100 | 100 | 54 | 98.9 | 96.7 | 97.8 |
| 26 | 97.7 | 97.7 | 100 | 56 | 100 | 100 | 100 |
| 28 | 100 | 95.7 | 95.7 | 58 | $98.7^{\dagger}$ | 98.0 | 99.3 |
| 30 | 98.0 | 94.1 | 96.0 | 60 | 100 | 98.0 | 98.0 |

${ }^{*} R R=\mathrm{d}-\operatorname{eff}_{P} / \mathrm{d}^{2}-\mathrm{eff}_{D}$, where d-eff ${ }_{P}$ and d-eff ${ }_{D}$ are the d-efficiencies for the proposed design and the D -optimal design, respectively.
$\dagger$ These designs are believed to be D-optimal, but have not been proved to be so.

If A-optimality is preferable (rather than the D-optimality), it can be shown that Property 4 holds:
Property 4: $\operatorname{tr}\left(X^{\prime} X\right)=2 \operatorname{tr}\left(X_{1}^{\prime} X_{1}\right)+2 \operatorname{tr}\left(X_{2}^{\prime} X_{2}\right)$.
Thus, to obtain the largest $\operatorname{tr}\left(X^{\prime} X\right)$, an A-optimal design should be employed for $X_{1}$ and $X_{2}$. Other optimalities can be investigated in a similar manner. Other criteria can be evaluated as well. For example, if average squared correlation (Miller and Sitter 2005) is considered, it can be shown that the proposed designs perform well in general.

Furthermore, a more general class is design of the form

$$
X=\left(\begin{array}{rr}
X_{1} & X_{2} \\
X_{3} & -X_{2}
\end{array}\right),
$$

where $X_{1} \neq X_{3}$. Since

$$
X^{\prime} X=\left(\begin{array}{rr}
X_{1}^{\prime} & X_{3}^{\prime} \\
X_{2}^{\prime} & -X_{2}^{\prime}
\end{array}\right) \times\left(\begin{array}{rr}
X_{1} & X_{2} \\
X_{3} & -X_{2}
\end{array}\right)=\left(\begin{array}{cc}
X_{1}^{\prime} X_{1}+X_{3}^{\prime} X_{3} & X_{1}^{\prime} X_{2}-X_{3}^{\prime} X_{2} \\
X_{2}^{\prime} X_{1}-X_{2}^{\prime} X_{3} & 2 X_{2}^{\prime} X_{2}
\end{array}\right),
$$

thus, if $X_{1}^{\prime} X_{2}-X_{3}^{\prime} X_{2}=0$, then main effects of factors in Group A will be orthogonal to main effects of factors in Group B. This deserves further investigation.

## Acknowledgments

Professor Jagdish N. Srivastava has been a true leader in our society and has been a strong supporter for young fellows. His original work on search design (among others) had a
siginificant impact on this work. It is our great privilege to contribute this work to this special issue in honor of Professor Srivastava. He will always be remembered. Thanks also go to two referees who provide a great set of constructive comments.

## References

Koukouvinos, C., M. Mitrouli, and J. Seberry. 2000. Bounds on the maximum determinant for ( $1,-1$ ) matrices. Bull. Inst. Combin. Appl., 29, 39-48.
Li, W., and D. K. Lin. 2003. Optimal foldover two-level fractional factorial designs. Technometrics, 45, 142-149.
Lin, D. K. 1993. Another look at first-order saturated designs: The p-efficient designs. Technometrics, 35, 284-292.
Miller, A., and R. Sitter. 2005. Using folded over non-orthogonal designs. Technometrics, 47, 502-513.

## Appendix A: Proofs for All Properties

## Proof of Property 1

1. Since factor $x_{i}$ is from Group A and factor $x_{j}$ from Group B, the corresponding columns are $\left(x_{1 i}, x_{2 i}, \ldots, x_{n / 2 i}, x_{1 i}, x_{2 i}, \ldots, x_{n / 2 i}\right)^{\prime}$ and $\left(x_{1 j}, x_{2 j}, \ldots, x_{n / 2 j},-x_{1 j}\right.$, $\left.-x_{2 j}, \ldots,-x_{n / 2 j}\right)^{\prime}$, respectively. The inner product of the two vectors is $\sum_{m=1}^{n / 2} x_{m i} \times$ $x_{m j}+\sum_{m=1}^{n / 2} x_{m i} \times\left(-x_{m j}\right)=0$.
2. (a) The interaction of two factors is $\left(x_{1 i} \times x_{1 j}, x_{2 i} \times x_{2 j}, \ldots, x_{n / 2 i} \times x_{n / 2 j}, x_{1 i} \times x_{1 j}, x_{2 i} \times\right.$ $\left.x_{2 j}, \ldots, x_{n / 2 i} \times x_{n / 2 j}\right)^{\prime}$; then the inner product of the main effect of factor $x_{k}$ and this interaction is $\sum_{m=1}^{n / 2} x_{m i} \times x_{m j} \times x_{m k}+\sum_{m=1}^{n / 2} x_{m i} \times x_{m j} \times\left(-x_{m k}\right)=0$.
(b) The interaction of two factors is $\left(x_{1 i} \times x_{1 j}, x_{2 i} \times x_{2 j}, \ldots, x_{n / 2 i} \times x_{n / 2 j},\left(-x_{1 i}\right) \times\right.$ $\left.\left(-x_{1 j}\right),\left(-x_{2 i}\right) \times\left(-x_{2 j}\right), \ldots,\left(-x_{n / 2 i}\right) \times\left(-x_{n / 2 j}\right)\right)^{\prime} ;$ then the inner product of the main effect of factor $x_{k}$ and this interaction is $\sum_{m=1}^{n / 2} x_{m i} \times x_{m j} \times x_{m k}+\sum_{m=1}^{n / 2}\left(-x_{m i}\right) \times$ $\left(-x_{m j}\right) \times\left(-x_{m k}\right)=0$.
(c) The two-factor interaction is $\left(x_{1 i} \times x_{1 j}, x_{2 i} \times x_{2 j}, \ldots, x_{n / 2 i} \times x_{n / 2 j},\left(-x_{1 i}\right) \times x_{1 j},\left(-x_{2 i}\right) \times\right.$ $\left.x_{2 j}, \ldots,\left(-x_{n / 2 i}\right) \times x_{n / 2 j}\right)^{\prime}$. Then the inner product of the main effect of factor $x_{k}$ and this interaction is $\sum_{m=1}^{n / 2} x_{m i} \times x_{m j} \times x_{m k}+\sum_{m=1}^{n / 2}\left(-x_{m i}\right) \times x_{m j} \times x_{m k}=0$.

## Proof of Property 2

For any square matrix, if $X$ is full rank, then $X$ must be full rank of its columns. Thus

$$
\operatorname{rank}\binom{X_{2}}{-X_{2}}=k_{2}
$$

where $X_{2}$ is an $(n / 2) \times k_{2}$ matrix. For an $(n / 2) \times 1$ vector with elements $\pm$, the largest number of linear independent vectors is $n / 2$.

If $k_{2}>n / 2$, there exists a set of $k_{2}$ scalars, $\alpha_{1}, \alpha_{2}, \ldots, \alpha_{k_{2}}$, not all zeros, such that

$$
\alpha_{1} \mathbf{x}_{21}+\alpha_{2} \mathbf{x}_{22}+\ldots+\alpha_{k_{2}} \mathbf{x}_{2 \mathbf{k}_{2}}=0
$$

where $\mathbf{x}_{\mathbf{2}}$ denotes the $i$ th column vector of $X_{2}, i=1,2, \ldots, k_{2}$. Then we have

$$
\alpha_{1}\binom{\mathbf{x}_{21}}{-\mathbf{x}_{\mathbf{2 1}}}+\alpha_{2}\binom{\mathbf{x}_{22}}{-\mathbf{x}_{22}}+\ldots+\alpha_{k_{2}}\binom{\mathbf{x}_{2 \mathbf{k}_{2}}}{-\mathbf{x}_{2 \mathbf{k}_{2}}}=0
$$

This implies that

$$
\operatorname{rank}\binom{X_{2}}{-X_{2}}<k_{2},
$$

which conflicts the proposition that

$$
\operatorname{rank}\binom{X_{2}}{-X_{2}}=k_{2} .
$$

Thus, $k_{2}$ must be $\leq n / 2$. Applying the same argument to $X_{1}$, we have $k_{1} \leq n / 2$. Since $k_{1}+k_{2}=n$, thus the claim of $k_{1}=k_{2}=n / 2$.

## Proof of Property 3

$$
X^{\prime} X=\left(\begin{array}{cc}
X_{1}^{\prime} & X_{1}^{\prime} \\
X_{2}^{\prime} & -X_{2}^{\prime}
\end{array}\right) \times\left(\begin{array}{cc}
X_{1} & X_{2} \\
X_{1} & -X_{2}
\end{array}\right)=\left(\begin{array}{cc}
2 X_{1}^{\prime} X_{1} & 0 \\
0 & 2 X_{2}^{\prime} X_{2}
\end{array}\right)
$$

Therefore,

$$
\left\|X^{\prime} X\right\|=\left\|\begin{array}{cc}
2 X_{1}^{\prime} X_{1} & 0 \\
0 & 2 X_{2}^{\prime} X_{2}
\end{array}\right\|=2^{n} \times\left\|X_{1}^{\prime} X_{1}\right\| \times\left\|X_{2}^{\prime} X_{2}\right\|
$$

## Proof of Property 4

Assume $\lambda$ is an eigenvalue of $X X$, we have $\left\|\lambda I_{n \times n}-X^{\prime} X\right\|=0$. Now,

$$
\begin{aligned}
\left\|\lambda I_{n \times n}-X^{\prime} X\right\| & =\left\|\left(\begin{array}{cc}
\lambda I_{n / 2 \times n / 2} & 0 \\
0 & \lambda I_{n / 2 \times n / 2}
\end{array}\right)-\left(\begin{array}{cc}
2 X_{1}^{\prime} X_{1} & 0 \\
0 & 2 X_{2}^{\prime} X_{2}
\end{array}\right)\right\| \\
& =\left\|\begin{array}{cc}
\lambda I_{n / 2 \times n / 2}-2 X_{1}^{\prime} X_{1} & \lambda I_{n / 2 \times n / 2}-2 X_{2}^{\prime} X_{2} \\
0 & \|
\end{array}\right\| \\
& =\left\|\lambda I_{n / 2 \times n / 2}-2 X_{1}^{\prime} X_{1}\right\| \times\left\|\lambda I_{n / 2 \times n / 2}-2 X_{2}^{\prime} X_{2}\right\| .
\end{aligned}
$$

Thus, $\left\|\lambda I_{n / 2 \times n / 2}-2 X_{1}^{\prime} X_{1}\right\| \times\left\|\lambda I_{n / 2 \times n / 2}-2 X_{2}^{\prime} X_{2}\right\|=0$. This implies that (a) $\lambda / 2$ is an eigenvalue of either $X_{1}^{\prime} X_{1}$ or $X_{2}^{\prime} X_{2}$ and (b) if $\lambda / 2$ is an eigenvalue of $X_{1}^{\prime} X_{1}$ or $X_{2}^{\prime} X_{2}$, then $\lambda$ is an eigenvalue of $X X$. So we have

$$
\operatorname{tr}\left(X^{\prime} X\right)=2 \operatorname{tr}\left(X_{1}^{\prime} X_{1}\right)+2 \operatorname{tr}\left(X_{2}^{\prime} X_{2}\right)
$$

## Appendix B: Comparisons of d-efficiencies between D-optimal design and the proposed design (for $\mathbf{6 2} \leq n \leq 120$, as a supplement to

Table 2.1)

Table 2
Comparisons of d-efficiencies between D-optimal design and the proposed design (for $62 \leq n \leq 120$ )

| $n$ | d-eff $_{D}(\%)$ | $\mathrm{d}-\mathrm{eff}_{P}(\%)$ | $\mathrm{RR}(\%)^{*}$ | $n$ | d-eff $_{D}(\%)$ | d-eff $_{P}(\%)$ | $\mathrm{RR}(\%)^{*}$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 62 | 99.1 | 97.0 | 97.9 | 92 | 100 | 98.7 | 98.7 |
| 64 | 100 | 100 | 100 | 94 | $94.1^{\dagger}$ | 97.9 | $104^{\ddagger}$ |
| 66 | 99.1 | 98.1 | 99.0 | 96 | 100 | 100 | 100 |
| 68 | 100 | 98.0 | 98.0 | 98 | 99.4 | 98.5 | 99.1 |
| 70 | $98.0^{\dagger}$ | 96.8 | 98.8 | 100 | 100 | 98.8 | 98.8 |
| 72 | 100 | 100 | 100 | 102 | 99.4 | 97.7 | 98.3 |
| 74 | 99.2 | 98.8 | 99.6 | 104 | 100 | 100 | 100 |
| 76 | 100 | 98.4 | 98.4 | 106 | $99.4^{\dagger}$ | 98.5 | 99.1 |
| 78 | $99.1^{\dagger}$ | 97.4 | 98.3 | 108 | 100 | 98.9 | 98.9 |
| 80 | 100 | 100 | 100 | 110 | 99.4 | 97.9 | 98.5 |
| 82 | 99.3 | 99.3 | 100 | 112 | 100 | 100 | 100 |
| 84 | 100 | 98.6 | 98.6 | 114 | 99.5 | 99.1 | 99.6 |
| 86 | 99.3 | 97.4 | 98.1 | 116 | 100 | 98.7 | 98.7 |
| 88 | 100 | 100 | 100 | 118 | 99.5 | 98.5 | 99.0 |
| 90 | 99.3 | 98.3 | 99.0 | 120 | 100 | 100 | 100 |

[^0]
[^0]:    ${ }^{*} R R=\mathrm{d}$-eff ${ }_{P} / \mathrm{d}$-eff ${ }_{D}$, where d-eff ${ }_{P}$ and d-eff ${ }_{D}$ are the d-efficiencies for the proposed design and the D -optimal design, respectively
    $\dagger$ These designs are believed to be D-optimal, but have not been proved to be so.
    $\ddagger$ The proposed design for $n=94$ is shown to have a higher d-efficiency than the published D-optimal design (see, for example, Koukouvinos, Mitrouli and Seberry (2000)).

