# ON ROBUSTNESS OF DESIGNS AGAINST INCOMPLETE DATA 

By SUBIR GHOSH<br>Indian Statistical Institute


#### Abstract

SUMMARY. In this paper, we characterize the robustness property of designs against incomplete data in the sense that, when any $t$ (a positive integer) observations are missing, all parameters are still estimable in the model assumed. We also present some examples of Srivastava-Chopra Optimum balanced resolution $V$ plans for $2^{m}$ factorials which are robust against missing of any two observations.


## 1. Introduction

The robustness of designs against incomplete data in case of missing of any single observation was first considered in Ghosh (1978). This paper gives a characterization of robustness property in the general case of missing of any $t$ observations. Some examples of designs robust against missing of any two observations are also presented.

## 2. Robust designs

Consider the ordinary linear model

$$
\begin{align*}
& E(\boldsymbol{y})=A \boldsymbol{\xi}  \tag{1}\\
& V(\boldsymbol{y})=\sigma^{2} I_{N}  \tag{2}\\
& \operatorname{Rank} \boldsymbol{A}=\nu \tag{3}
\end{align*}
$$

where $\boldsymbol{y}(N \times 1)$ is a vector of observations, $\boldsymbol{A}(N \times \nu)$ is a known matrix, $\boldsymbol{\xi}(\nu \times 1)$ is a vector of fixed unknown parameters and $\sigma^{2}$ is a constant which may or may not be known. Let $T$ be the underlying design corresponding to $\boldsymbol{y}$.

Definition 1: A design under the model (1-3) is said to be robust against missing of any $t$ (a positive integer) observations if the ( $N-t \times \nu$ ) matrix obtained from $\boldsymbol{A}$ by omitting any $t$ rows has rank $\nu$. It is clear from definition 1 that $N$ must at least be $\nu+t$. Suppose $N=\nu+k$, where $k(\geqslant t)$ a positive integer. Clearly, there exist $k$ linearly independent vectors $\boldsymbol{C}_{\boldsymbol{i}}^{\prime}=\left(C_{i_{1}}, \ldots, C_{\mathbf{i N}_{N}}\right)$, $i=1, \ldots, k$, with real elements satisfying

$$
\begin{equation*}
C_{i}^{\prime} A=0 \tag{4}
\end{equation*}
$$

Consider the $(k \times N)$ matrix

$$
\boldsymbol{C}=\left[\begin{array}{cccccc}
C_{11} & C_{12} & \ldots & C_{1 t} & \ldots & C_{1 N}  \tag{5}\\
C_{21} & C_{22} & \ldots & C_{2 t} & \ldots & C_{2 N} \\
C_{k 1} & C_{k 2} & \ldots & C_{k t} & & \ldots
\end{array} C_{k N} .\right]
$$

whose $i$-th row is $\boldsymbol{C}_{\boldsymbol{i}}^{\prime}$ and furthermore, Rank $\boldsymbol{C}=k$. We now recall that a matrix $\boldsymbol{B}$ is said to have the property $P_{t}$ if no $t$ columns of $B$ are linearly dependent. The following theorem characterizes the robustness property.

Theorem 1: Let $T$ be a design under (1-3) with $N=v+k$ observations, where $k(\geqslant t)$ a positive integer. Then, $T$ is robust against missing of any $t$ observations if and only if (iff) the matrix $\boldsymbol{C}$, defined in (5), has the property $P_{\boldsymbol{t}}$.

Proof: Suppose $\boldsymbol{C}$ has $\boldsymbol{P}_{\boldsymbol{t}}$. Let

$$
A=\left[\begin{array}{c}
\boldsymbol{A}_{1}  \tag{6}\\
\dddot{\boldsymbol{A}_{2}}
\end{array}\right], \quad \boldsymbol{C}=\left[\boldsymbol{C}_{\mathbf{1}}^{*}: \boldsymbol{C}_{\mathbf{2}}^{*}\right],
$$

where $\boldsymbol{A}_{1}(t \times \nu), \boldsymbol{A}_{\mathbf{2}}(\overline{N-t} \times \nu), \boldsymbol{C}_{\mathbf{1}}^{*}(k \times t)$ and $\boldsymbol{C}_{\mathbf{2}}^{*}(k \times \overline{N-t})$.
We have, from (4),

$$
\begin{equation*}
\boldsymbol{C}_{1}^{*} \boldsymbol{A}_{1}+\boldsymbol{C}_{2}^{*} \boldsymbol{A}_{2}=0 \tag{7}
\end{equation*}
$$

Suppose

$$
C_{1}^{*}=\left[\begin{array}{l}
C_{11}^{*}  \tag{8}\\
C_{12}^{*}
\end{array}\right], \quad C_{2}^{*}=\left[\begin{array}{l}
C_{21}^{*} \\
C_{\Sigma 2}^{*}
\end{array}\right]
$$

where $\boldsymbol{C}_{11}^{*}(t \times t), \quad \boldsymbol{C}_{12}^{*}(\overline{k-t} \times t), \boldsymbol{C}_{21}^{*}(t \times \overline{N-t})$, and $\boldsymbol{C}_{22}^{*}(\overline{k-t} \times \overline{N-t})$; Suppose, furthermore, Rank $\left(C_{11}^{*}\right)=t$. Thus, we get

$$
\begin{equation*}
\boldsymbol{C}_{11}^{*} \boldsymbol{A}_{1}+\boldsymbol{C}_{21}^{*} \boldsymbol{A}_{2}=0 \tag{9}
\end{equation*}
$$

Hence,

$$
\begin{equation*}
A_{1}=-C_{11}^{*-1} C_{21}^{*} A_{2} \tag{10}
\end{equation*}
$$

Thus, the rows of $\boldsymbol{A}_{1}$ are linear combinations of the rows in $\boldsymbol{A}_{2}$. Therefore, the matrix $\boldsymbol{A}_{2}$ obtained from $\boldsymbol{A}$ by omitting $t$ rows in $\boldsymbol{A}_{1}$, has rank $\nu$. The argument is similar for any other set of $t$ rows of $A$. Hence the design $T$ is robust.

Suppose the design $T$ is robust against missing of $t$ observations. Then, there is a $(t \times \overline{N-t})$ matrix $\boldsymbol{D}$ satisfying

$$
\begin{equation*}
\boldsymbol{A}_{1}=\boldsymbol{D} \boldsymbol{A}_{2} \tag{l1}
\end{equation*}
$$

i.e.,

$$
\left[\boldsymbol{I}_{t}:-\boldsymbol{D}\right]\left[\begin{array}{l}
\boldsymbol{A}_{1}  \tag{12}\\
\boldsymbol{A}_{2}
\end{array}\right]=0
$$

Considering (4), (6), and (9), it follows that there exists a $(t \times k)$ matrix $\boldsymbol{U}$ such that

$$
\begin{equation*}
\boldsymbol{U} C_{1}^{*}=\boldsymbol{I}_{t}, \quad \boldsymbol{U} \boldsymbol{C}_{2}^{*}=-\boldsymbol{D} \tag{13}
\end{equation*}
$$

It is now easy to check that $\operatorname{Rank}\left(\boldsymbol{C}_{1}^{*}\right)=t$. Therefore $\boldsymbol{C}$ has $\boldsymbol{P}_{t}$. This completes the proof of the theorem.

The following results are of practical importance.
Corollary 1: Suppose $t=1$. The design $T$ is robust against missing of any one observation iff $\boldsymbol{C}(k \times N)$ has the property $P_{1}$ or, in other words,

$$
\left\langle C_{1 j}, C_{2 j}, \ldots, C_{k j}\right) \neq(0,0, \ldots, 0) \text { for }(j=1, \ldots, N)
$$

(i.e., none of the column vectors in $C$ is a null vector).

Corollary 2: Suppose $t=2$. The design $T$ is robust against missing of any two observations iff $\boldsymbol{C}(k \times N)$ has the property $P_{2}$, or in other words,
(i) $\quad\left(C_{1 j}, C_{2 j}, \ldots, C_{k j}\right) \neq(0,0, \ldots, 0)$ for $(j=1, \ldots, N)$,
(ii) $\quad\left(C_{1 j}, C_{2 j}, \ldots, C_{k j}\right) \neq w\left(C_{1 j^{\prime}}, C_{2 j^{\prime}}, \ldots, C_{k j^{\prime}}\right)$,
where $j \neq j^{\prime},\left(j, j^{\prime}=1, \ldots, N\right)$, and $w$ is a real constant .
It is to be remarked that the above results are also true in case $\boldsymbol{A}(N \times M)$, $\xi(M \times 1)$ and $\operatorname{Rank}(\boldsymbol{A})=\nu<\min (M, N)$.

## 3. EXAMPLES FROM $2^{m}$ factorials

Consider a $2^{m}$ factorial experiment. The treatments are denoted by $\left(x_{1}, x_{2}, \ldots, x_{m}\right)$, where $x_{i}=0$ or 1 . We denote a design with $N$ treatments by a $(N \times m)$ matrix $\boldsymbol{T}$ whose rows are treatments. Optimal balanced resolution $V$ plans for $2^{m}$ factorials, $4 \leqslant m \leqslant 8$, and for practical values of $N$, have been presented in the papers of Srivastava and/or Chopra.

By 'weight' of a vector, we mean the number of nonzero elements in it. Let $S_{i}$ be the set of all $(1 \times m)$ vectors, with elements 0 and 1 , of weight $i$ $(i=0,1, \ldots, m) . \quad$ Clearly the number of members in $S_{i}$ is $\binom{m}{i}$.

Srivastava-Chopra designs are denoted by $\boldsymbol{\lambda}^{\prime}=\left(\lambda_{0}, \lambda_{1}, \ldots, \lambda_{m}\right)$ where $\lambda_{i}$ is the number of times the set $S_{i}$ occurs in the design. Thus $N=\sum_{i=0}^{m}\binom{m}{i} \lambda_{i}$. These optimum designs may or may not remain optimum or even resolution $V$ plans when some observations are missing. We now present, as example, designs which are robust against missing of any $t$ observations. These designs remain as resolution $V$ plans when any $t$ observations are missing.

Example 1: Consider $m=4, N=15$. Here, $\nu=11$. Thus $k=4$. The design is represented as $\boldsymbol{\lambda}^{\prime}=\left(\begin{array}{lllll}1 & 1 & 1 & 1 & 0\end{array}\right)$. The matrix $\boldsymbol{C}$ is given below

$$
\boldsymbol{C}=\left[\begin{array}{rrrrrrrrrrrrrrr}
1 & -3 & -3 & -3 & -3 & 2 & 2 & 2 & 2 & 2 & 2 & -1 & -1 & -1 & -1 \\
0 & 1 & -1 & 1 & -1 & 0 & -2 & 0 & 0 & 2 & 0 & 1 & -1 & 1 & -1 \\
0 & 1 & -1 & -1 & 1 & 0 & 0 & -2 & 2 & 0 & 0 & -1 & 1 & 1 & -1 \\
0 & 1 & 1 & 1 & -1 & -2 & 0 & 0 & 0 & 0 & 2 & 1 & 1 & -1 & -1
\end{array}\right)
$$

It is easy to check that the above matrix has the property $P_{2}$ but not $P_{3}$. Thus the present design is robust against missing of any two observations and not robust against missing of any three observations. Clearly for $N=16$, the design $\boldsymbol{\lambda}^{\prime}=\left(\begin{array}{lllll}1 & 1 & 1 & 1 & 1\end{array}\right)$ is also robust against missing of two observations.

Example 2: Consider $m=5, N=22 a$. We have $\nu=16$ and thus $(k=6)$. The design is given by $\boldsymbol{\lambda}^{\prime}=\left(\begin{array}{llllll}1 & 1 & 1 & 0 & 1 & 1\end{array}\right)$. We present the matrix C below

$$
\boldsymbol{C}=\left[\begin{array}{rrrrrrrrrrrrrrrrrrrrr}
3 & -3 & -3 & -3 & -3 & -3 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & -3 & -3 & -3 & -3 & -3 \\
-3 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & -1 & -1 \\
0 & -2 & 2 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & -1 & -1 & -1 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 \\
0 & -2 & 0 & 2 & 0 & 0 & 1 & 0 & 1 & 1 & -1 & 0 & 0 & -1 & -1 & 0 & 1 & 0 & -1 & 0 & 0 \\
0 & -2 & 0 & 0 & 2 & 0 & 1 & 1 & 0 & 1 & 0 & -1 & 0 & -1 & 0 & -1 & 1 & 0 & 0 & -1 & 0 \\
0 & -2 & 0 & 0 & 0 & 2 & 1 & 1 & 1 & 0 & 0 & 0 & -1 & 0 & -1 & -1 & 1 & 0 & 0 & 0 & -1
\end{array} 00\right\}
$$

Obsorve that the above matrix has the property $P_{2}$ and, therefore, this design is robust against missing of any two observations. It is clear that the designs $\quad N=23 a, \quad \lambda^{\prime}=\left(\begin{array}{lllll}2 & 1 & 1 & 1\end{array}\right), \quad N=24 a, \lambda^{\prime}=\left(\begin{array}{llll}2 & 1 & 1 & 0\end{array}\right.$ 12), and $N=25 a, \lambda^{\prime}=\left(\begin{array}{lllll}3 & 1 & 1 & 0 & 1\end{array} 2\right)$ have the same property.

## Refereinces

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