























A New Class of Supersaturated Designs
Dennis K. J. Lin Department of Statistics The University of Tennessee Knoxville, TN 37996
Supersaturated designs are useful in situations in which the number of active factors is very small compared to the total number of factors being considered. In this article, a new class of supersaturated designs is constructed using half fractions of Hadamard matrices. When a Hadamard matrix of order <i>N</i> is used, such a design can investigate up to $N - 2$ factors in $N/2$ runs. Results are given for $N \le 60$. Extension to larger <i>N</i> is straightforward. These designs are superior to other existing supersaturated designs and are easy to construct. An example with real data is used to illustrate the ideas.
KEY WORDS: Hadamard matrices; Plackett and Burman designs; Random balance designs.
UTK Technical Report 1991

Web of Science®	VANCED RCH								
Citing ArticlesSummary << Return to previous Summary page A NEW CLASS OF SUPERSATURATED DESIGNS LIN DKJ TECHNOMETRICS 35: 28-31 1993 These documents in the database cite the above record:									
Refine your results Subject Categories Source Titles Document Types Authors Publication Years more choices 94 results found Go to Page: 1 of 10 Records 1 10 Show 10 per page									
 Use the checkboxes to select records for output. See the sidebar Qin H, Zhang SL, Fang KT Constructing uniform designs with two- or three-level ACTA MATHEMATICA SCIENTIA 26 (3): 451-459 JUL 2 Times Cited: 0 Context Sensitive Links Luo XH, Stefanski LA, Boos DD 	for options. 006 Image: White the second se								







							Ha	lf F	ractio	on o	f Wi	lliar	n's (1968	3) D	ata								
Factor																								
Run 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	У
1 +	+	+	-	-	-	+	+	+	+	+	-	+	-	-	+	+	-	-	+	-	-	-	+	133
2 +	-	-	-	-	-	+	+	+	-	-	-	+	+	+	+	-	+	-	-	+	+	-	-	62
3 +	+	-	+	+	-	-	-	-	+	-	+	+	+	+	+	+	-	-	-	-	+	+	-	45
4 +	+	-	+	-	+	-	-	-	+	+	-	+	-	+	+	-	+	+	+	-	-	-	-	52
5 -	-	+	+	+	+	-	+	+	-	-	-	+	-	+	+	+	-	-	+	-	+	+	+	56
6 -	-	+	+	+	+	+	-	+	+	+	-	-	+	+	-	+	+	+	+	+	+	-	-	47
7 -	-	-	-	+	-	-	+	-	+	-	+	+	+	-	+	+	+	+	+	+	-	-	+	88
8 -	+	+	-	-	+	-	+	-	+	-	-	-	-	-	-	-	-	+	-	+	+	+	-	193
9 -	-	-	-	-	+	+	-	-	-	+	+	-	-	+	-	+	+	-	-	-	-	+	+	32
10 +	+	+	+	-	+	+	+	-	-	-	+	-	+	+	-	+	-	+	-	+	-	-	+	53
11 -	+	-	+	+	-	-	+	+	-	+	-	-	+	-	-	-	+	+	-	-	-	+	+	276
12 +	-	-	-	+	+	+	-	+	+	+	+	+	-	-	+	-	-	+	-	+	+	+	+	145
13 +	+	+	+	+	-	+	-	+	-	-	+	-	-	-	-	-	+	-	+	+	-	+	-	130
14 -	-	+	-	-	-	-	-	-	-	+	+	-	+	-	-	-	-	-	+	-	+	-	-	127









	Table 34.1 Assig	Inme	ent Ar	ray								
	Class				Group	I.				Gro		
	Factor	A	B	C	D	E	F	G	Н	J	L	M
	Experi- ment No.	(9)	(10)	(12)	(13)	(5)	(1)	(2)	(3)	(5)	(1)	(2)
	1-3	1	1	1	1	1	1	1	1	3	1	1
	2-4	2	2	2	2	2	1	1	2	1	1	2
	3-15	3	3	3	3	3	1	1	3	3	2	2
	4-10	2	2	3	3	1	1	2	2	1	2	1
	5 - 7	3	3	1	1	2	1	2	3	1	1	3
	6-22	1	1	2	2	3	1	2	1	1	3	2
	7-5	3	3	2	2	1	1	3	2	2	1	2
	8-2	1	1	3	3	2	1	3	1	2	1	1
	9-19	2	2	1	1	3	1	3	3	1	3	1
	10-9	2	3	2	3	1	2	1	3	3	1	3
	11-17	3	1	3	1	2	2	1	1	2	2	3
	12-27	1	2	1	2	3	2	1	2	3	3	3
	13 - 26	3	1	1	2	1	2	2	2	2	3	3
	14 - 24	1	2	2	3	2	2	2	1	3	3	2
	15-8	2	3	3	1	3	2	2	3	2	1	3
Random	16 - 12	1	2	3	1	1	2	3	2	3	2	1
	17 - 23	2	3	1	2	2	2	3	1	2	3	2
Balance	18-21	3	1	2	3	3	2	3	3	3	3	1
	19-14	3	2	3	2	1	3	1	3	2	2	2
Design	20-1	1	3	1	3	2	3	1	1	1	1	1
8	21-11	2	1	2	1	3	3	1	2	2	2	1
	22 - 25	1	3	2	1	1	3	2	2	1	3	3
$T_{actual} (1096)$	23 - 18	2	1	3	2	2	3	2	1	3	2	3
1 agueni (1980)	24-13	3	2	1	3	3	3	2	3	1	2	2
	25 - 16	2	1	1	3	1	3	3	1	1	2	3
	26 - 6	3	2	2	1	2	3	3	2	3	1	2
	27 - 20	1	3	3	2	3	3	3	3	2	3	1











Example:
$$E(f_{NOD})$$

$$E(f_{NOD}) = \sum_{1 \le i < j \le m} f_{NOD}^{ij} / {m \choose 2}$$
where $f_{NOD}^{ij} = \sum_{u=1}^{q_i} \sum_{v=1}^{q_j} \left(n_{uv}^{(ij)} - \frac{n}{q_i q_j} \right)^2$

Lower Bound of
$$E(f_{NOD})$$

Theorem 1. For any design $X \in \mathcal{U}(n; q_1, \dots, q_m)$,
 $E(f_{NOD}) = \frac{\sum_{k,l=1,k\neq l}^n \lambda_{kl}^2}{m(m-1)} + C(n, q_1, \dots, q_m)$
 $\geq \frac{n(\sum_{j=1}^m n/q_j - m)^2}{m(m-1)(n-1)} + C(n, q_1, \dots, q_m)$,
where $C(n, q_1, \dots, q_m) = \frac{nm}{m-1} - \frac{1}{m(m-1)} \left(\sum_{i=1}^m \frac{n^2}{q_i} + \sum_{i,j=1,j\neq i}^m \frac{n^2}{q_i q_j} \right)$













rable r. Supe	ersaturated design	ns derived fro	$m L_{16}(4^5)$	(using 1 a	as the brar	ching colu	umn)
$S(12; 3^14^4)$	$S(8;2^14^4)$	Row	1	2	3	4	5
1		1	1	1	1	1	1
2		2	1	2	2	2	2
3		3	1	3	3	3	3
4		4	1	4	4	4	4
5	1	5	2	1	2	3	4
6	2	6	2	2	1	4	3
7	3	7	2	3	4	1	2
8	4	8	2	4	3	2	1
	5	9	3	1	3	4	2
	6	10	3	2	4	3	1
	7	11	3	3	1	2	4
	8	12	3	4	2	1	3
9		13	4	1	4	2	3
10		14	4	2	3	1	4
11		15	4	3	2	4	1
12		16	4	4	1	3	2

	UD		OD		SSD
	[11]		[0000]		[0000 0000]
	27		0111		01112021
	33		0222		0222 0222
	49		1012		10122210
$U \oplus L =$	55	⊕	1120	=X=	1120 1120
	6 6		1201		1201 1201
	7 2		2021		2021 0111
	88		2102		2102 2102
	94		2210		2210 1012





$$\begin{aligned} & \textbf{Penalized Least Squares} \text{ (Li and Lin, 2003)} \\ & \textbf{Model} \\ & Y_i = \mathbf{x}_i^T \boldsymbol{\beta} + \varepsilon_i \\ & \textbf{Penalized Likelihood (Fan and Li, 1999)} \\ & \frac{1}{n} \sum_{i=1}^n \log f(y_i, \mathbf{x}_i^T \boldsymbol{\beta}) - \sum_{j=1}^d p_\lambda(|\beta_j|) \\ & \textbf{Becomes} \\ & Q(\boldsymbol{\beta}) \equiv \frac{1}{2n} \sum_{i=1}^n (Y_i - \mathbf{x}_i^T \boldsymbol{\beta})^2 + \sum_{j=1}^d p_\lambda(|\beta_j|) \end{aligned}$$

Choices of
$$p_{\lambda}$$

$$Q(\beta) = \frac{1}{2n} \sum_{i=1}^{n} (Y_i - \mathbf{x}_i^T \beta)^2 + \sum_{j=1}^{d} p_{\lambda}(|\beta_j|)$$

$$\bullet \mathsf{L}_1 \text{ penalty (Donoho and Johnstone, 1994)}$$

$$\bullet \mathsf{L}_2 \text{ penalty (Donoho and Johnstone, 1994)}$$

$$\bullet \mathsf{L}_2 \text{ penalty & \mathsf{L}_q \text{ penalty (Frank and Friedman, 1993)}$$

$$\bullet p_{\lambda}(|\beta|) = \lambda \frac{|\beta|^2}{2}$$

$$\bullet \text{ Hard Thresholding penalty}$$

$$p_{\lambda}(|\beta|) = \lambda^2 - (|\beta| - \lambda)^2 I(|\beta| < \lambda)$$







Supersaturated Designs with High Searching Probability (Chatterjee, Bhavana and Lin, 2006) $\mathbf{y} = 1\mu + T_1(\zeta_0)\zeta_0 + \epsilon, \quad V(\epsilon) = \sigma^2 I$ Theorem For any $\zeta_0 \subset \xi_2$ and $\zeta(\neq \zeta_0)$, we have $P(h(\zeta_0, \mathbf{y}) > h(\zeta, \mathbf{y})) = G_d(x, \rho)$ $= 1 - \Phi_d(\rho\sqrt{(n-x)/2}) - \Phi_d(\rho\sqrt{(n+x)/2}) + 2\Phi_d(\rho\sqrt{(n-x)/2}) \Phi_d(\rho\sqrt{(n+x)/2})$ where $x = t(\zeta_0)'t(\zeta), \ \rho = \zeta_0/\sigma$ and Φ is the distribution function of N(0, 1). Supersaturated Designs with High Searching Probability (Chatterjee, Bhavana and Lin, 2006)

	2							
n	m	1	1.2	1.4	1.6	1.8	2	Reference
6	10	0.9022	0.9477	0.9737	0.9875	0.9944	0.9976	L&D (2004)
8	21	0.9153	0.9537	0.9759	0.9881	0.9945	0.9977	L&D (2004)
10	15	0.9194	0.9548	0.9761	0.9882	0.9945	0.9977	B&C (2004)
12	16	0.975	0.9915	0.9974	0.9993	0.9998	0.9999	B&C (1962)
12	22	0.9207	0.9551	0.9761	0.9882	0.9945	0.9977	Lin(1993)
12	24	0.9207	0.9551	0.9761	0.9882	0.9945	0.9977	B&C (1962)
12	66	0.975	0.9915	0.9974	0.9993	0.9998	0.9999	Lin (1995)
14	19	0.9765	0.9917	0.9974	0.9993	0.9998	0.9999	B&C (2004)













