

# Optimal Designs for Estimation of Ratio of Variance Components in Diallel Crosses

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## Abstract

The results on optimal designs for diallel crosses are presently available for the standard fixed effects linear model. In some cases, however, parental lines may be randomly selected from a population of lines resulting in a random effects model. Ghosh and Das (2003) discussed  $A$ -optimal designs in this context for estimation of heritability. In this paper we first propose an unbiased estimator of the ratio of the variance components which has a one-to-one relation with heritability. We then obtain an expression of the variance of this unbiased estimator of the ratio of variance components. Through minimization of the variance we obtain optimal designs and show certain connections with the optimization problem under the fixed effects model.

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## 1 Introduction

Plant breeders frequently need overall information on average performance of individual inbred lines in crosses known as general combining ability. For this purpose diallel crossing techniques are employed. Griffing (1956) defines a model for diallel crosses in terms of genotypic values where the breeding value of the cross  $(i, j)$  is expressed as the sum of general combining abilities for the two lines. In certain contexts, specific combining ability effects representing the interaction between lines  $i$  and  $j$  in a cross  $(i, j)$  are

also included in the model; see Kempthorne (1969) and Mayo (1980) for details.

Accordingly the analysis of the observations arising out of  $n$  crosses involving  $p$  lines is carried out by postulating a model

$$Y_{ijl} = \mu + g_i + g_j + e_{ijl}; \quad i < j \quad (1.1)$$

where  $Y_{ijl}$  is the observation arising out of the  $l$ -th replication of the cross  $(i, j)$ ,  $g_i$  is the  $i$ -th line effect with  $E(g_i) = 0$ ,  $Var(g_i) = \sigma_g^2 \geq 0$ ,  $Cov(g_i, g_j) = 0$ ,  $\mu$  is the general mean and  $e_{ijl}$  is the random error component, uncorrelated with  $g_i$ , with expectation zero and variance  $\sigma_e^2 > 0$ ,  $1 \leq i < j \leq p$ . Here  $\mu, \sigma_e^2$  and  $\sigma_g^2$  are unknown parameters. Also, the specific combining ability effects are assumed to be negligible and have been absorbed in the error component. In the model, (1.1),  $\mu$  is a fixed effect while  $g_i, g_j$  ( $i < j$ ) and  $e_{ijl}$  are random effects.

Our primary interest is in *heritability*,  $h^2$ , which is defined as  $h^2 = 4\sigma_g^2 / (2\sigma_g^2 + \sigma_e^2)$ . Such a measure expresses the extent to which individual phenotypes are determined by genotypes. In order to get a good estimator of  $h^2$  we propose optimal designs for unbiased estimation of  $\sigma_g^2 / \sigma_e^2$  since  $h^2 = \frac{4\sigma_g^2}{2\sigma_g^2 + \sigma_e^2} = \frac{4(\sigma_g^2 / \sigma_e^2)}{2(\sigma_g^2 / \sigma_e^2) + 1}$ . Let  $T$  be an unbiased estimator of  $\sigma_g^2 / \sigma_e^2$ . Then an estimator of  $h^2$  is  $4T / (2T + 1)$ . Hence an unbiased estimator of  $\sigma_g^2 / \sigma_e^2$  will lead to a asymptotically unbiased estimator of  $h^2$ .

The results on optimal designs for diallel crosses are presently available for the standard fixed effects linear model. In some cases, however, parental lines may be randomly selected from a population of lines resulting in a random effects model. In this context, under a random effects model Ghosh and Das (2003) obtained an estimator of the ratio of the variance components. In order to address the issue of optimal designs they considered the  $A$ -optimality criteria for the estimation of heritability in the sense that the designs minimize the sum of the variances of the estimators of the variance components.

In this paper we first propose an unbiased estimator  $T$  of  $\sigma_g^2 / \sigma_e^2$ . We then obtain an expression of the variance of  $T$ . The large sample variance of  $4T / (2T + 1)$  is proportional to the variance of  $T$ , the proportionality constant being a function of  $\sigma_g^2 / \sigma_e^2$ . Through minimization of the variance of  $T$  we obtain optimal designs and show certain connections with the optimization problem under the fixed effects model.

## 2 Unbiased Estimation of Ratio of Variance Components and their Variances

Consider a diallel cross experiment carried out using a design  $d$  with  $p$  lines and  $b$  blocks each having  $k$  crosses. Our model is

$$Y = \mu \mathbf{1}_n + D_2' \beta + D_1' g + e \quad (2.1)$$

where  $Y$  is the vector of  $bk$  ( $= n$ ) observations,  $\mu$  is the general mean,  $g$  is the  $p \times 1$  vector of general combining ability effects with  $IE(g) = 0$  and  $ID(g) = \sigma_g^2 I$ ,  $\beta$  is the fixed effect due to blocks and  $e$  is the error vector with  $IE(e) = 0$  and  $ID(e) = \sigma_e^2 I$ . Also,  $D_1 = (d_{uv}^{(1)})$  is the  $p \times n$  line versus observation incidence matrix with  $d_{uv}^{(1)} = 1$  if  $v$ -th observation is out of a cross involving the  $u$ -th line and  $d_{uv}^{(1)} = 0$  otherwise. Similarly,  $D_2 = (d_{uv}^{(2)})$  is the  $b \times n$  block versus observation incidence matrix with  $d_{uv}^{(2)} = 1$  if the  $v$ -th observation arise from the  $u$ -th block and  $d_{uv}^{(2)} = 0$  otherwise. Here  $\mathbf{1}_t$  represents a  $t \times 1$  column vector of all ones and  $I_t$  denotes an identity matrix of order  $t$ . In situations where the order is evident from the context, we write respectively  $\mathbf{1}$  and  $I$  instead of  $\mathbf{1}_t$  and  $I_t$ . Thus,  $IE(Y) = \mu \mathbf{1}_n + D_2' \beta$ ,  $ID(Y | \sigma_g^2, \sigma_e^2) = \sigma_g^2 D_1' D_1 + \sigma_e^2 I_n$ . We assume that  $Y \sim N_n(\mu \mathbf{1}_n + D_2' \beta, \sigma_g^2 D_1' D_1 + \sigma_e^2 I_n)$ , where  $N_n(\theta, \Sigma)$  denotes  $n$ -variate normal distribution with mean vector  $\theta$  and dispersion matrix  $\Sigma$ . Let  $s = (s_1, s_2, \dots, s_p)'$  where  $s_i$  is the replication of the  $i$ -th line. Also, for  $i \neq j$ , let  $g_{ij}$  be the number of times cross  $(i, j)$  appears in the design, and  $g_{ii} = s_i$ . Then it is easy to see that  $D_1 D_1' = G = (g_{ij})$  and  $D_1 \mathbf{1} = s$ . Let  $N = D_1 D_2' = (n_{ij})$  be the incidence matrix with  $n_{ij}$  indicating the number of times the  $i$ -th line occurs in the  $j$ -th block. For such a design  $d$ , let  $C_d = G - k^{-1} N N'$ .  $C_d$  is also called the  $C$ -matrix of the design  $d$ .

Following Das and Ghosh (2003) and Searle et. al. (1992), expected value of sum of squares due to lines ( $SSL$ ) and the expected value of sum of squares due to error ( $SSE$ ) have

$$IE \begin{bmatrix} SSL \\ SSE \end{bmatrix} = L \begin{pmatrix} \sigma_g^2 \\ \sigma_e^2 \end{pmatrix} \quad (2.2)$$

where

$$L = \begin{pmatrix} \text{tr}(C_d) & p-1 \\ 0 & n-b-p+1 \end{pmatrix}$$

and for a square matrix  $A$ ,  $\text{tr}(A)$  stands for the trace. Also,

$$\begin{aligned} & \mathbb{D} \begin{pmatrix} SSL \\ SSE \end{pmatrix} \\ &= \begin{pmatrix} 2\{\sigma_g^4 \text{tr}(C_d^2) + 2\sigma_e^2 \sigma_g^2 \text{tr}(C_d) + \sigma_e^4 (p-1)\} & 0 \\ 0 & 2(n-b-p+1) \sigma_e^4 \end{pmatrix}. \end{aligned} \quad (2.3)$$

Then,

$$\mathbb{D} \begin{pmatrix} \hat{\sigma}_g^2 \\ \hat{\sigma}_e^2 \end{pmatrix} = L^{-1} \mathbb{D} \begin{pmatrix} SSL \\ SSE \end{pmatrix} (L^{-1})' = 2 \begin{pmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{pmatrix} \quad (2.4)$$

where

$$t_{11} = \{(n-b-p+1)(\sigma_g^4 \text{tr}(C_d^2) + 2\sigma_e^2 \sigma_g^2 \text{tr}(C_d) + \sigma_e^4) + \sigma_e^4 (p-1)^2\} / \{(n-b-p+1) \text{tr}^2(C_d)\},$$

$$t_{12} = t_{21} = -\sigma_e^4 (p-1) / \{(n-b-p+1) \text{tr}(C_d)\},$$

$$\text{and } t_{22} = \sigma_e^4 / (n-b-p+1).$$

**THEOREM 2.1.** For a design  $d$ , an unbiased estimator of  $\sigma_g^2/\sigma_e^2$  is

$$T = \frac{(n-b-p-1)(SSL/SSE) - p+1}{\text{tr}(C_d)}.$$

**PROOF.** Note that  $SSE/\sigma_e^2 \sim \chi_{n-b-p+1}^2$  and is distributed independently of  $SSL$ . Furthermore,  $E(1/(SSE/\sigma_e^2)) = 1/(n-b-p-1)$ . Thus,

$$\begin{aligned} E(SSL/SSE) &= E(SSL)E(1/SSE) = \sigma_e^{-2} E(SSL)E(1/(SSE/\sigma_e^2)) \\ &= \sigma_e^{-2} E(SSL)/(n-b-p-1). \end{aligned}$$

Now using Equation (2.2) we get

$$\begin{aligned} E(SSL/SSE) &= \sigma_e^{-2} (\sigma_g^2 \text{tr}(C_d) + \sigma_e^2 (p-1)) / (n-b-p-1) \\ &= ((\sigma_g^2/\sigma_e^2) \text{tr}(C_d) + (p-1)) / (n-b-p-1) \end{aligned}$$

and the theorem is established.  $\square$

We have considered the estimator  $T$  because of it being simple and unbiased. However, other estimators with better properties may exist. This estimation problem is open for further research.

**THEOREM 2.2.** *Let  $d$  be a design with  $p$  lines,  $b$  blocks each of size  $k$ . Then, the variance of  $T$  is*

$$V(T; d, \sigma_g^2, \sigma_e^2) = \alpha \left\{ (n-b-p-1) \sigma_g^4 \frac{\text{tr}(C_d^2)}{\text{tr}^2(C_d)} + 2t \sigma_e^2 \sigma_g^2 \frac{1}{\text{tr}(C_d)} + t(p-1) \sigma_e^4 \frac{1}{\text{tr}^2(C_d)} + \sigma_g^4 \right\} \quad (2.5)$$

where  $\alpha = 2/\{(n-b-p-3)\sigma_e^4\}$  and  $t = n-b-2$ .

**PROOF.** In view of Theorem 2.1,  $\text{Var}(T) = \frac{(n-b-p-1)^2}{\text{tr}^2(C_d)} \text{Var}(SSL/SSE)$ .

Now,

$$\text{Var}(SSL/SSE) = E(SSL/SSE)^2 - E^2(SSL/SSE). \quad (2.6)$$

The second term in (2.6) can be obtained from Theorem 2.1 itself and is given by  $E^2(SSL/SSE) = \{(\sigma_g^2/\sigma_e^2)\text{tr}(C_d) + (p-1)\}/(n-b-p-1)\}^2$ . For the first term, since  $SSL$  and  $SSE$  are distributed independently,  $E(SSL/SSE)^2 = E(SSL^2) E(1/SSE^2)$ . Now from Equation (2.2) and (2.3),

$$\begin{aligned} E(SSL^2) &= \text{Var}(SSL) + E^2(SSL) \\ &= 2\{\sigma_g^4 \text{tr}(C_d^2) + 2\sigma_e^2 \sigma_g^2 \text{tr}(C_d) + \sigma_e^4 (p-1)\} \\ &\quad + \{\sigma_g^2 \text{tr}(C_d) + \sigma_e^2 (p-1)\}^2. \end{aligned}$$

Also,  $E(1/SSE^2) = E(1/(SSE/\sigma_e^2)^2)/\sigma_e^4$ . Now, since  $SSE/\sigma_e^2 \sim \chi_{n-b-p-1}^2$ , it is easy to see that  $E(1/(SSE/\sigma_e^2)^2) = 1/\{(n-b-p-1)(n-b-p-3)\}$ . Substituting the above expressions in (2.6), we get the desired result.  $\square$

The results for estimation of  $\sigma_g^2/\sigma_e^2$  and the corresponding variance expression under unblocked diallel cross experiments can be obtained as a special case of the above results by taking the number of blocks as one. For example, the unbiased estimator of  $\sigma_g^2/\sigma_e^2$  under an unblocked model, using a design  $d_0$  with  $p$  lines and  $n$  crosses, reduces to  $\{(n-p-2)(SSL/SSE) - p+1\}/\text{tr}(C_{0d_0})$  where  $C_{0d_0} = G - \frac{1}{n}ss'$ , is the  $C$ -matrix of  $d_0$ .

### 3 Optimal Designs

A diallel cross experiment is said to be complete if each of the  $\binom{p}{2}$  crosses appear equally often in the experiment, otherwise it is said to be a partial diallel cross experiment. Let  $\mathcal{D}(p, b, k)$  be the class of diallel cross designs with  $p$  lines arranged in  $b$  blocks of  $k$  crosses each and  $\mathcal{D}(p, n)$

the class of unblocked designs for diallel crosses involving  $p$  lines and  $n$  crosses. Also, for  $2n/p$  an integer,  $\mathcal{D}_0(p, n)$  denotes the subclass of designs in  $\mathcal{D}(p, n)$  with  $s_i = 2n/p : i = 1, \dots, p$ . In fact, among designs in  $\mathcal{D}(p, n)$ , only designs in the subclass  $\mathcal{D}_0(p, n)$  have maximal  $\text{tr}(C_{0d})$ . Finally, let  $\mathcal{D}_0(p, b, k)$  be the subclass of designs in  $\mathcal{D}(p, b, k)$  for which  $\text{tr}(C_d)$  is maximum.

A design  $d$  is said to be optimal if, among all designs in  $\mathcal{D}$ ,  $d$  minimizes the variance of  $T$ . From 2.5 it then follows that an optimal design in  $\mathcal{D}(p, b, k)$  minimizes  $\text{tr}(C_d^2)/\text{tr}^2(C_d)$  and  $1/\text{tr}(C_d)$ . In other words, from 2.5 we observe that the minimization problem addressed in Ghosh and Das (2003) is analogous to the minimization of variance of  $T$ . Thus,  $A$ -optimal designs obtained in Ghosh and Das (2003) are also optimal for the minimization of the variance of  $T$ . Analogous results hold in the unblocked situation since in order to minimize the variance of  $T$ , within the class of designs  $\mathcal{D}(p, n)$ , it is sufficient to minimize  $\text{tr}(C_{0d}^2)/\text{tr}^2(C_{0d})$  and  $1/\text{tr}(C_{0d})$ .

In view of the above,  $A$ -optimal designs in Ghosh and Das (2003) are optimal for the estimation of  $\sigma_g^2/\sigma_e^2$ . Thus we have the following results on optimal designs for estimation of  $\sigma_g^2/\sigma_e^2$ .

(i) Complete diallel cross designs in  $\mathcal{D}(p, n)$  are optimal.

(ii) The existence of a nested balanced incomplete block (NBIB) design  $d$  with parameters  $v = p, b_1 = b, b_2 = bk, k_1 = 2k, k_2 = 2$  yields an optimal incomplete block design  $d^*$  for diallel crosses. The construction methods and elaborate tables of NBIB designs are available in a review paper by Morgan et al. (2001). The tables in their paper provide solutions to our optimal diallel cross designs within the parametric range  $2k < p < 16, bk \leq 15p$ . The case  $2k = p$  is dealt in Gupta and Kageyama (1994). The NBIB designs have been extended to nested balanced block designs and a series of designs, optimal under our setup, is given in Das et al. (1998).

(iii) Das et al. (1998) gave two general methods of construction of block designs for partial diallel crosses. Their designs belong to  $\mathcal{D}_0(p, b, k)$  with  $2k/p$  an integer. The designs are optimal in  $\mathcal{D}_0(p, b, k)$ .

(iv) For unblocked designs, partial diallel cross designs in which every line appears  $2n/p$  times and each cross appears either  $\lambda = [2n/\{p(p-1)\}]$  or  $\lambda + 1$  times are optimal. A common way to construct such a design is to form crosses between the two treatments in each block of a conventional binary incomplete block design with  $p$  treatments each occurring  $2n/p$  times,

$n$  distinct blocks of size 2 each and treatment concurrences  $\lambda$  and  $\lambda+1$ . This includes the  $M$ -designs of Singh and Hinkelmann (1995), the first series of designs of Mukerjee (1997), and some designs listed in Das et al. (1998).

(v) As a result of the very nature of the derived objective function under the random effects model that is being minimized, every previously known  $MS$ -optimal design under the fixed effects model (Das et al., 1998) would also be optimal under our set-up.

Optimal partial diallel crosses listed above necessarily have orthogonal blocks. A diallel cross design is said to be orthogonally blocked if each line occurs in every block  $r/b$  times where  $r$  is the constant replication number of the lines in the design; see Gupta et. al.(1995). In general, for non-orthogonal block designs, Mukerjee (1997) has provided some methods for constructing efficient partial diallel crosses. Let  $p = n_1 n_2$  where  $n_1 \geq 2, n_2 \geq 3$ . Partition the set  $\{1, 2, \dots, p\}$  into  $n_1$  mutually exclusive and exhaustive subsets  $\{S_1, S_2, \dots, S_{n_1}\}$  each of cardinality  $n_2$ . Let

$$d_0^{**} = \{(i, j) : 1 \leq i < j \leq p \text{ and } i, j \in S_u \text{ for some } u\}. \quad (3.1)$$

In the construction of the block design  $d^{**}$  with  $p (= n_1 n_2)$  lines, the lines are denoted by  $a_j^u, 1 \leq u \leq n_1, 0 \leq j \leq n_2 - 1$ . In 3.1 take  $S_u = \{a_0^u, a_1^u, \dots, a_{n_2-1}^u\}$ . Then from Equation (3.1)  $d_0^{**}$  consists of  $n_1 n_2 (n_2 - 1)/2$  crosses where in a cross the two lines are from the same  $S_u$ . For  $n_2 (\geq 5)$  odd, Mukerjee's general approach for grouping the crosses in  $d_0^{**}$  into blocks is now given.

Let  $M_1$  be the incidence matrix of a general block design  $d_1$  involving  $n_1$  treatments and  $n_2$  blocks such that each block has size  $n_1$  and each treatment is replicated  $n_2$  times. For  $1 \leq u \leq n_1, 0 \leq l \leq n_2 - 1$ , in the  $l$ -th occurrence of treatment  $u$  in  $d_1$ , replace treatment  $u$  by the  $(n_2 - 1)/2$  crosses  $\{(a_{j+l}^u, a_{n_2-j+l}^u) : 1 \leq j \leq (n_2 - 1)/2\}$ , where  $j+l$  and  $n_2 - j+l$  are reduced mod  $n_2$ . The resulting block design,  $d^{**}$ , for diallel crosses belongs to  $\mathcal{D}(n_1 n_2, n_2, n_1 (n_2 - 1)/2)$  and represents a partitioning of the crosses in  $d_0^{**}$  into blocks.

EXAMPLE. Let  $n_1 = 3, n_2 = 5$ . Then  $p = 15, b = 5, k = 6$  and the design with rows as blocks is:

$$\begin{aligned} & [(a_1^1, a_4^1), (a_2^1, a_3^1), (a_1^2, a_4^2), (a_2^2, a_3^2), (a_1^3, a_4^3), (a_2^3, a_3^3)] \\ & [(a_2^1, a_0^1), (a_3^1, a_4^1), (a_2^2, a_0^2), (a_3^2, a_4^2), (a_2^3, a_0^3), (a_3^3, a_4^3)] \end{aligned}$$

$$\begin{aligned} & \{(a_3^1, a_1^1), (a_4^1, a_0^1), (a_3^2, a_1^2), (a_4^2, a_0^2), (a_3^3, a_1^3), (a_4^3, a_0^3)\} \\ & \{(a_1^1, a_2^1), (a_0^1, a_1^1), (a_4^2, a_2^2), (a_0^2, a_1^2), (a_4^3, a_2^3), (a_0^3, a_1^3)\} \\ & \{(a_0^1, a_3^1), (a_1^1, a_2^1), (a_0^2, a_3^2), (a_1^2, a_2^2), (a_0^3, a_3^3), (a_1^3, a_2^3)\} \end{aligned}$$

Let, for a block design  $d$ ,  $\lambda_{d1} \leq \lambda_{d2} \leq \dots \leq \lambda_{d(p-1)}$  be the non-zero eigenvalues of the information matrix  $C_d$ . Then, after some algebra, we find that for  $i = 1, \dots, n_2 - 1$ ,  $\lambda_{d^{*-i}} = n_2 - 2 - \frac{2}{n_2 - 1}$ , for  $i = n_2, \dots, p - n_1$ ,  $\lambda_{d^{*-i}} = n_2 - 2$  and for  $i = p - n_1 + 1, \dots, p - 1$ ,  $\lambda_{d^{*-i}} = 2(n_2 - 1)$  with  $d^{**} \in \mathcal{D}(p, n_2, \frac{n_1(n_2-1)}{2})$ .

We now give lower bounds to efficiency of non-orthogonal block designs  $d^{**}$  for estimating ratio of variance components. For  $p = n_1 n_2$ ,  $b = n_2$ ,  $k = n_1(n_2 - 1)/2$ , we first obtain the lower bounds to efficiency with respect to the competing classes  $\mathcal{D}_0(p, b, k)$ . Note that for a block design  $d \in \mathcal{D}_0(p, b, k)$  for diallel crosses,  $\text{tr}(C_d) = 2b(k - 1)$ . Mukerjee (1997) has shown that  $\lambda_{d_01} \leq n_2 - 2$  where  $\lambda_{d_01}$  is the minimum nonzero eigenvalue of  $C_{d_0}$ , with  $d_0 \in \mathcal{D}(n_1 n_2, n_1 n_2(n_2 - 1)/2)$ . Thus, it follows that,  $\lambda_{d1} \leq \lambda_{d_01} \leq n_2 - 2$  where  $d \in \mathcal{D}(n_1 n_2, n_2, n_1(n_2 - 1)/2)$  and  $d_0$  is the design ignoring the block classification of the design  $d$ . Also, we know that for  $d \in \mathcal{D}_0(p, b, k)$ ,  $\text{tr}(C_d^2)$  is minimum when  $\lambda_{di} = 2b(k - 1)/(p - 1)$ ,  $i = 1, \dots, p - 1$ . However,  $2b(k - 1)/(p - 1) = n_2 - 2 + \{n_2(n_1 - 1) - 2\}/(p - 1)$ . Thus, in our design setup, for block designs  $d \in \mathcal{D}_0(p, b, k)$ , with  $n_1 > 1$ , it follows that  $\text{tr}(C_d^2) = \sum_{i=1}^{p-1} \lambda_{di}^2 \geq (n_2 - 2)^2 + \{2b(k - 1) - (n_2 - 2)\}^2/(p - 2) = W_0$ , say. Thus, for a design  $d \in \mathcal{D}_0(p, b, k)$  with  $n_1, n_2, \sigma_g^2, \sigma_e^2$  fixed, from 2.5, a lower bound to  $V(T; d, \sigma_g^2, \sigma_e^2)$  is obtained by substituting  $W_0$  and  $2b(k - 1)$  for  $\text{tr}(C_d^2)$  and  $\text{tr}(C_d)$ , respectively. We denote this lower bound by  $V_0^*(T; n_1, n_2, \sigma_g^2, \sigma_e^2)$ .

Thus, from 2.5, for given  $n_1, n_2, \sigma_g^2$  and  $\sigma_e^2$ , the  $A$ -efficiency of the design  $d^{**} \in \mathcal{D}_0(p, b, k)$  is at least as large as  $e_{A_0}(n_1, n_2, \sigma_g^2, \sigma_e^2)$  where

$$e_{A_0}(n_1, n_2, \sigma_g^2, \sigma_e^2) = \frac{V_0^*(T; n_1, n_2, \sigma_g^2, \sigma_e^2)}{V(T; d^{**}, \sigma_g^2, \sigma_e^2)} \quad (3.2)$$

The denominator is obtained by substituting the values of  $\lambda_{d^{*-i}}$ , in  $\text{tr}(C_{d^{**}}^2)$ . Also,  $\text{tr}(C_{d^{**}}) = 2b(k - 1)$ .

Now, for any  $d \in \mathcal{D}(p, b, k)$ , where  $p, b, k$  are arbitrary but fixed, it is easy to see that  $\text{tr}(C_d^2)/\text{tr}^2(C_d) \geq 1/(p - 1) = W$ , say. Also, we know that  $\text{tr}(C_d)$  is bounded above by  $k^{-1}b\{2k(k - 1 - 2x) + px(x + 1)\}$ , where  $x$  is



the largest integer not exceeding  $2k/p$  (see Das et. al., 1998). Thus, for a design  $d \in \mathcal{D}(p, b, k)$  with  $p, b, k, \sigma_g^2, \sigma_e^2$  fixed, from 2.5, a lower bound to  $V(T; d, \sigma_g^2, \sigma_e^2)$  is obtained by substituting  $W$  for  $\frac{\text{tr}(C_d^2)}{\text{tr}^2(C_d)}$  and substituting  $k^{-1}b\{2k(k-1-2x) + px(x+1)\}$  for  $\text{tr}(C_d)$ . We denote this lower bound by  $V^*(T; p, b, k, \sigma_g^2, \sigma_e^2)$ .

Thus, from 2.5, for given  $p, b, k, \sigma_g^2$  and  $\sigma_e^2$ , the  $A$ -efficiency of a design  $d^\# \in \mathcal{D}(p, b, k)$  is at least as large as  $e_A(p, b, k, \sigma_g^2, \sigma_e^2)$  where

$$e_A(p, b, k, \sigma_g^2, \sigma_e^2) = \frac{V^*(T; p, b, k, \sigma_g^2, \sigma_e^2)}{V(T; d^\#, \sigma_g^2, \sigma_e^2)} \quad (3.3)$$

As earlier, the denominator is obtained by substituting the actual values of  $\text{tr}(C_{d^\#})$  and  $\text{tr}(C_{d^\#}^2)$  for the design  $d^\#$ .

Under classes  $\mathcal{D}_0(p, b, k)$  and  $\mathcal{D}(p, b, k)$ , using 3.2 and 3.3, we obtained the lower bounds to efficiency of  $d^{**}$  for  $2 \leq n_1 \leq 15$  and  $5 \leq n_2 \leq 15$  with  $n_2$  odd. Here, each of  $\sigma_g^2$  and  $\sigma_e^2$  has been taken within the range of  $(0.1, 3.0)$ , with increments of 0.1. It is observed that efficiencies are greater than 0.90 in both cases when  $2 \leq n_1 \leq 15$ ,  $5 < n_2 \leq 15$ . Furthermore, the efficiencies are greater than 0.95 for 43.9% of the parametric sets with  $2 \leq n_1 \leq 15$ ,  $5 < n_2 \leq 15$  and both  $\sigma_g^2, \sigma_e^2$  in the range of  $(0.1, 3.0)$ . For the parametric range  $2 \leq n_1 \leq 15$  and  $n_2 = 5$ , (i) efficiencies are more than 0.90 when  $2 \leq n_1 \leq 4$ , (ii) 94.2% of the designs with  $5 \leq n_1 \leq 15$  have efficiencies greater than 0.9, (iii) the efficiencies are atleast 0.893. We observe that the efficiencies are generally robust against the values of variance components, and depends only on design parameters.

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## References

- DAS, A., DEAN, A.M. and GUPTA, S. (1998). On optimality of some partial diallel cross designs. *Sankhyā Ser. B*, **60**, 511-524.
- DAS, A., DEY, A. and DEAN, A.M. (1998). Optimal block designs for diallel cross experiments. *Statist. Probab. Lett.*, **36**, 427-436.
- GHOSH, H. and DAS, A. (2003). Optimal diallel cross designs for estimation of heritability. *J. Statist. Plann. Inference*, **116**, 185-196.
- GRIFFING, B. (1956). Concepts of general and specific combining ability in relation to diallel crossing systems. *Aust. J. Bio. Sci.*, **9**, 463-493.

- GUPTA, S., DAS, A. and KAGEYAMA S. (1995). Single replicate orthogonal block designs for circulant partial diallel crosses. *Commun. Statist. Theory Meth.*, **24**, 2601-2607.
- GUPTA, S. and KAGEYAMA, S. (1994). Optimal complete diallel crosses. *Biometrika*, **81**, 420-424.
- KEMPTHORNE, O. (1969). *An Introduction to Genetic Statistics*. The Iowa State University Press, Iowa.
- MAYO, O. (1980). *The Theory of Plant Breeding*. Clarendon Press, Oxford.
- MORGAN, J.P., PREECE, D.A. and REES, D.H. (2001). Nested balanced incomplete block designs. *Discrete Math.*, **231**, 351-389.
- MUKERJEE, R. (1997). Optimal partial diallel crosses. *Biometrika*, **84**, 939-948.
- SEARLE, S.R., CASELLA, G. and MCCULLOCH, C.E. (1992). *Variance Components*. Wiley, New York.
- SINGH, M. and HINKELMANN, K. (1995). Partial diallel crosses in incomplete blocks. *Biometrics*, **51**, 1302-1314.

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