

**USE OF SOME FUNCTIONS OF SPACINGS IN THE ESTIMATION OF  
COMMON SCALE PARAMETER OF NORMAL AND DOUBLE  
EXPONENTIAL DISTRIBUTIONS**

R.S. Priya and P. Yageen Thomas

**ABSTRACT**

In this paper we consider the problem of best linear unbiased estimation and best linear invariant estimation of the common scale parameter of a normal and double exponential distributions using some functions of spacings of all observations of individual samples. We have also proved a sufficient condition for the non-negativity of the common scale estimator obtained by the above method. Further we have obtained necessary and sufficient condition for the derived estimators to be constant multiple of the sum of first and last spacings of pooled sample.

**1. INTRODUCTION**

It is well-known that order statistics are very useful in the estimation of location and scale parameters of a distribution. For a survey of literature on the application of order statistics in estimating the location and scale parameters of distributions, see, Balakrishnan and Cohen (1991) and David and Nagaraja (2003).

For a discussion on the problem of estimation of common location and common scale parameters of several distributions using order statistics of the pooled sample is given in Sajeevkumar and Thomas (2005). Arnold et al. (1992, p.174), observed that the existence and uniqueness of the BLUE for the scale parameter of a distribution do not guarantee that it is always non-negative. Balakrishnan and Papadatos (2002) have given a simpler formula for the *BLUE* of the scale parameter of a distribution using spacings. Further they have proved a sufficient condition for their estimator to be positive. Sajeev kumar and Thomas (2010) have extended the method proposed by Balakrishnan and Papadatos (2002) to estimate the common scale parameter  $\sigma$  of several distributions by spacings of order statistics of inid random variables.

**2. MOTIVATION FOR ESTIMATING THE COMMON SCALE  
PARAMETER OF SEVERAL SYMMETRIC DISTRIBUTIONS BY  
USING SOME FUNCTIONS OF SPACINGS**

Let  $X_{i1}, X_{i2}, \dots, X_{in_i}$  be  $n_i$  independent observations drawn from a population with distribution function denoted by  $F_i\left(\frac{x_i - \mu}{\sigma}\right)$ ,  $i = 1, 2, \dots, k$ ,  $-\infty < \mu < \infty$ ,  $\sigma > 0$ . Let  $X_{1:n}, X_{2:n}, \dots, X_{n:n}$  be the corresponding order statistics of the pooled sample of all  $n = n_1 + \dots + n_k$  observations. Now if we write  $Y_{r:n} = \left(\frac{X_{r:n} - \mu}{\sigma}\right)$ ,  $r = 1, 2, \dots, n$ , then  $(Y_{1:n}, Y_{2:n}, \dots, Y_{n:n})$  is distributed identically same as the order statistics of the pooled sample of  $k$  independent random samples of which  $n_i$  are drawn from the distribution with distribution function  $F_i(y)$ ,  $i = 1, 2, \dots, k$ . Then the distribution theory of  $(Y_{1:n}, Y_{2:n}, \dots, Y_{n:n})$  can be dealt with using the result of Vaughan and Venables (1972).

Now we consider the case when the basic distributions are all symmetrically distributed about the common location parameter  $\mu$ , Then from Bapat and Beg (1989) the distributions of  $\underline{Y} = (Y_{1:n}, Y_{2:n}, \dots, Y_{n:n})$  and  $(-Y_{n:n}, -Y_{n-1:n}, \dots, -Y_{1:n})$  are identical.

Now define  $W_j = X_{j+1:n} - X_{j:n}$ , and  $W_j^* = Y_{j+1:n} - Y_{j:n}$ ,  $j = 1, 2, \dots, n-1$ ,  $R_i = W_i + W_{n-i}$  and  $R_i^* = W_i^* + W_{n-i}^*$ ,  $i = 1, 2, \dots, [n/2]$ , where  $[.]$  is the usual greatest integer function. Clearly  $W_j^* \stackrel{d}{=} W_{n-j}^*$ ,  $j = 1, 2, \dots, n-1$ .

Thus if we write  $\underline{W}^* = (W_1^*, W_2^*, \dots, W_{n-1}^*)'$  then  $\underline{W}^* \stackrel{d}{=} J\underline{W}^*$ , where

$$J = \begin{bmatrix} 0 & 0 & \cdot & \cdot & \cdot & 0 & 1 \\ 0 & 0 & \cdot & \cdot & \cdot & 1 & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & 0 & \cdot & \cdot & \cdot & 0 & 0 \end{bmatrix}$$

is a square matrix of order  $n-1$ .

Let the expectation of the vector  $\underline{W}^* = (W_1^*, W_2^*, \dots, W_{n-1}^*)'$  and its variance-covariance matrix  $D(\underline{W}^*)$  be given by

$$E(\underline{W}^*) = \underline{\alpha}, \quad (2.1)$$

(where  $E(W_j^*) = \alpha_j$ ,  $j = 1, 2, \dots, n-1$  and

$$D(\underline{W}^*) = B \quad (2.2)$$

Also

$$S = E(\underline{W}^* \underline{W}^{*'}) \quad (2.3)$$

Clearly  $B$  and  $S$  are square matrices of order  $n-1$ . Also the elements of  $\underline{\alpha}$ ,  $B$  and  $S$  are free of  $\mu$  and  $\sigma$ . Clearly

$$E(J\underline{W}^*) = J\underline{\alpha} \quad (2.4)$$

And hence we have

$$\underline{\alpha} = J\underline{\alpha}, \quad (2.5)$$

Also  $D(J\underline{W}^*) = JBJ$  and hence

$$B = JBJ \quad (2.6)$$

Left multiplication of  $B$  by  $J$  changes the  $i$ -th row into  $(n-i)$ -th row and right multiplication of  $B$  by  $J$  changes the  $j$ -th column into  $(n-j)$ -th column. Then from (2.6) it is seen that if the  $j$ -th column vector of  $B$  is  $(c_1, c_2, \dots, c_{n-1})'$ , then its  $(n-j)$ -th column vector is  $(c_{n-1}, c_{n-2}, \dots, c_1)'$ . Similarly if the  $i$ -th row of  $B$  is  $(r_1, r_2, \dots, r_{n-1})$  then its  $(n-i)$ -th row is  $(r_{n-1}, r_{n-2}, \dots, r_1)$ .

Also from the identity  $J = J^{-1} = J'$  we get

$$B^{-1} = JB^{-1}J \quad (2.7)$$

Thus we see that the property described for  $B$  is true for  $B^{-1}$  also.

Now the best linear unbiased estimator for the common scale parameter  $\sigma$  using spacings of order statistics of pooled sample of all observations are given by (see Sajeevkumar and Thomas 2010)

$$L_U = (\underline{\alpha}' B^{-1} \underline{\alpha})^{-1} \underline{\alpha}' B^{-1} \underline{W} \quad (2.8)$$

And

$$\text{Var}(L_U) = (\underline{\alpha}' B^{-1} \underline{\alpha})^{-1} \sigma^2, \quad (2.9)$$

where  $\underline{W} = (W_1, W_2, \dots, W_{n-1})$ .

Also the best linear invariant estimator for the common scale parameter  $\sigma$  using spacings of order statistics of the pooled sample of all observations and corresponding  $MSE$  are given by (see, Sajeevkumar and Thomas 2010)

$$L_I = \underline{\alpha}' S^{-1} \underline{W} \quad (2.10)$$

and corresponding  $MSE$  is given by

$$MSE(L_I) = (1 - \underline{\alpha}' S^{-1} \underline{\alpha}) \sigma^2 \quad (2.11)$$

The connection between  $BLUE$  and  $BLIE$  of  $\sigma$  is given by (See, Sajeevkumar and Thomas 2010)

$$L_I = a L_U, \quad (2.12)$$

Where  $a$  is a constant ( $0 < a < 1$ ) and is given by  $a = \underline{\alpha}' S^{-1} \underline{\alpha}$ .

Clearly the form of the vector  $\underline{\alpha}$  is  $\underline{\alpha}' = (\alpha_1, \alpha_2, \dots, \alpha_{[n/2]}, \alpha_{[n/2]-1}, \dots, \alpha_1)$  for  $n$  even and  $\underline{\alpha}' = (\alpha_1, \alpha_2, \dots, \alpha_{[n/2]}, \alpha_{[n/2]}, \dots, \alpha_1)$  for  $n$  odd, where  $[.]$  is the usual greatest integer function. Using this property of  $\underline{\alpha}$  we see that the coefficients of  $W_j$  and  $W_{n-j}$  in the estimator  $L_U$  defined in (2.8) are identically equal. This property of  $L_U$  proves that  $BLUE$  of  $\sigma$  reduce to a linear function of spacings namely  $R_i = W_i + W_{n-i}, i = 1, 2, \dots, [n/2]$  Using (2.12) clearly  $BLIE$  of  $\sigma$  also reduce to a linear function of spacings of pooled sample namely  $R_i = W_i + W_{n-i}, i = 1, 2, \dots, [n/2]$ . Thus there is some advantage in using  $R_i, i = 1, 2, \dots, [n/2]$  in estimating  $\sigma$  by an estimate which involves a covariance matrix of order  $[n/2]$  only where as in (2.8) an equivalent estimate involves a covariance matrix of order  $n-1$ . In section 3 we derived an estimator of  $\sigma$  and its variance based on  $R_i, i = 1, 2, \dots, [n/2]$ .

### 3. BLUE AND BLIE FOR THE SCALE COMMON PARAMETER USING SOME FUNCTIONS OF SPACINGS

In section 2 we have proved that if the parent distributions are symmetric about the common location parameter  $\mu$  then the  $BLUE$  of common scale parameter  $\sigma$  reduces to some function of spacings. Hence there exist constants  $c_i^*$   $i = 1, 2, \dots, [n/2]$ , such that

$$L = \sum_{i=1}^{[n/2]} c_i^* R_i = \sigma \sum_{i=1}^{[n/2]} c_i^* R_i^*, \tag{3.1}$$

Let  $\underline{R}^* = (R_1^*, R_2^*, \dots, R_{[n/2]}^*)'$  be the random vectors of functions of spacings of the pooled sample from the completely known  $F_0(y)$  and use the notation

$$M = E(\underline{R}^*), H = D(\underline{R}^*), Q = E(\underline{R}^* \underline{R}^{*'}), \tag{3.2}$$

where  $D(\underline{\xi})$  denotes the dispersion matrix of the random vector  $\underline{\xi}$ . Clearly

$$H = Q - \underline{M} \underline{M}', \quad H > 0, \quad Q > 0 \tag{3.3}$$

Now we have the following

Proposition 3.1: Under the above assumptions and the notation of this section, the BLUE of the common scale parameter  $\sigma$  and its variance are given by

$$L_u = \frac{\underline{M}' H^{-1}}{\underline{M}' H^{-1} \underline{M}} \underline{R} \quad \text{with} \quad \text{Var}(L_u) = \frac{\sigma^2}{\underline{M}' H^{-1} \underline{M}} \tag{3.4}$$

where  $\underline{R} = (R_1, R_2, \dots, R_{[n/2]})'$ .

Proof: Since the form of the most general location-invariant estimator of  $\sigma$  is  $L = \underline{c}' \underline{R}$ , where  $\underline{c} = (c_1, c_2, \dots, c_{[n/2]})'$ , it follows that it is unbiased for  $\sigma$  if and only if

$$\underline{c}' \underline{M} = 1 \tag{3.5}$$

On the other hand its variance is given by

$$\text{Var}(L) = (\underline{c}' H \underline{c}) \sigma^2. \tag{3.6}$$

Thus we wish to minimize (3.6) under restriction (3.5). Taking into the account the Lagrangian  $(Q(\underline{c}; \lambda)) = \underline{c}' H \underline{c} - 2\lambda(\underline{c}' \underline{M})$ , it is easy to see that the optimal value is  $\underline{c} = \lambda(H^{-1} \underline{M})$  and the restriction yields  $\lambda = \frac{1}{\underline{M}' H^{-1} \underline{M}}$ ; this completes

the proof.

Now the BLIE of the common scale parameter using function of spacings is given by the following theorem.

Proposition 3.2: Under the above assumptions and the notation of this section, the BLIE of the common scale parameter  $\sigma$  and its MSE are given by,

$$L_I = \underline{M}' Q^{-1} \underline{R} \quad \text{with } MSE(L_I) = (1 - \underline{M}' Q^{-1} \underline{M}) \sigma^2. \quad (3.7)$$

The proof follows by the same arguments as in proposition 3.1, except that we do not have to use restriction(3.5).

The connection between *BLUE* and *BLIE* of the common scale parameter  $\sigma$  is given in the following proposition.

Proposition 3.3. There exist a constant  $a$ ,  $0 < a < 1$ , independent of  $\mu$  and  $\sigma$  such that

$$L_I = a L_u \quad (3.8)$$

This constant is given by

$$a = \underline{M}' Q^{-1} \underline{M} = \frac{\underline{M}' Q^{-1} \underline{M}}{1 + \underline{M}' Q^{-1} \underline{M}}. \quad (3.9)$$

Proof: First note that  $Q = H + \underline{M} \underline{M}'$  (See equation 3.3). Thus, by theorem 8.9.3 in Graybill(1969) implies that  $Q^{-1} = H^{-1} - \frac{1}{1 + \underline{M}' H^{-1} \underline{M}} (H^{-1} \underline{M})(H^{-1} \underline{M})'$

and thus  $\underline{M}' Q^{-1} \underline{M} = \underline{M}' H^{-1} \underline{M} - \frac{(\underline{M}' H^{-1} \underline{M})^2}{1 + \underline{M}' H^{-1} \underline{M}}$ , proving the second equality

in (3.9). Consider now the class of estimators of the form  $L_\lambda = \lambda L_u$ ,  $\lambda \in R$ . It is easy to see that they are linear invariant estimators and, moreover, that

$$MSE(L_\lambda) = E(\lambda L_u - \sigma)^2 = \left( \frac{\lambda^2}{\underline{M}' H^{-1} \underline{M}} + (1 - \lambda)^2 \right) \sigma^2. \quad \text{Therefore, minimizing}$$

the last expression with respect to  $\lambda$ , we get  $\lambda = \frac{\underline{M}' H^{-1} \underline{M}}{1 + \underline{M}' H^{-1} \underline{M}} = a \in (0,1)$ . For

this value of  $\lambda = a$  it follows that

$$MSE(L_a) = \frac{\sigma^2}{1 + \underline{M}' H^{-1} \underline{M}} = (1 - \underline{M}' Q^{-1} \underline{M}) \sigma^2 = MSE(L_I). \text{ Hence the proof.}$$

**4. CONDITION FOR WHICH BLUE (OR BLIE) OF THE SCALE PARAMETER  $\sigma$  IS A MULTIPLE OF  $R_1 = W_1 + W_{n-1}$  AND NON-NEGATIVE**

In this section, we obtain, necessary and sufficient conditions under which the BLUE (or, equivalently, the BLIE) of the common scale parameter  $\sigma$  is a constant multiple of  $R_1 = W_1 + W_{n-1} = X_{2:n} - X_{1:n} + X_{n:n} - X_{n-1:n}$ . (Clearly when  $n=2$  then  $R_1$  reduces to twice sample range and when  $n=3$  then  $R_1$  reduces to sample range), have also proved the non-negativity for the scale estimator  $L_u$  of  $\sigma$ . In particular we shall prove the following.

**Theorem 4.1:** The BLUE (or the BLIE) of the common scale parameter  $\sigma$  is a constant multiple of  $R_1$  if and only if any one of the following equivalent conditions hold.

- (i). There exist a constant  $\lambda_1$  such that  $\underline{M} = \lambda_1(\underline{Qn})$ , where  $\underline{n} = (1, 0, \dots, 0)$ , vector of order  $[n/2]$ .
- (ii). There exist a constant  $\lambda_1$  such that  $E(R_i^*) = \lambda_1 E(R_i^* R_1^*)$ ,  $i = 1, \dots, [n/2]$ , where  $R_1^* = W_1^* + W_{n-1}^* = Y_{2:n} - Y_{1:n} + Y_{n:n} - Y_{n-1:n}$ .
- (iii). There exist a constant  $\lambda_2$  such that  $\underline{M} = \lambda_2(\underline{Hn})$ .
- (iv). There exist a constant  $\lambda_2$  such that  $E(R_i^*) = \lambda_2 Cov(R_i^* R_1^*)$ ,  $i = 1, \dots, [n/2]$ , where  $R_1^*$  is as defined in (ii).

When (i)-(iv) hold, the BLUE of  $\sigma$  is given by

$$L_u = \left[ \frac{X_{2:n} - X_{1:n} + X_{n:n} - X_{n-1:n}}{\lambda_1(\underline{n}, \underline{Qn})} \right] = \left[ \frac{X_{2:n} - X_{1:n} + X_{n:n} - X_{n-1:n}}{\lambda_2(\underline{n}, \underline{Hn})} \right]$$

and the BLIE of the common scale parameter  $\sigma$  is

$$L_l = \lambda_1 (X_{2:n} - X_{1:n} + X_{n:n} - X_{n-1:n}) = \left[ \frac{\lambda_2 (X_{2:n} - X_{1:n} + X_{n:n} - X_{n-1:n})}{1 + \lambda_2^2(\underline{n}, \underline{Hn})} \right].$$

**Proof:** First observe that (i) is equivalent to (ii) and (iii) is equivalent to (iv). If (ii) holds, then  $E(R_i^*)(1 - \lambda_1)E(R_1^*) = \lambda_1 Cov(R_i^* R_1^*)$ ,  $i = 1, \dots, [n/2]$ ,

which can be rewritten as  $E(R_i^*) = \lambda_2 \text{Cov}(R_i^*, R_1^*)$ ,  $i=1, \dots, [n/2]$  where

$$\lambda_2 = \frac{\lambda_1}{1 - \lambda_1 E(R_1^*)} \text{ and thus, (iv) holds (observe that } \lambda_1 = \frac{E(R_1^*)}{E(R_1^{*2})}, \text{ since}$$

$$E(R_1^*) = \sum_{i=1}^{[n/2]} E(R_i^*) = \lambda_1 \sum_{i=1}^{[n/2]} E(R_i^* R_1^*) = \lambda_1 E(R_1^{*2}) \text{ and hence } 0 < \lambda_1 E(R_1^*) < 1.$$

Conversely, if (iv) holds, then

$$E(R_1^*) = \sum_{i=1}^{[n/2]} E(R_i^*) = \lambda_2 \sum_{i=1}^{[n/2]} \text{Cov}(R_i^*, R_1^*) = \lambda_2 \text{Var}(R_1^*)$$

showing that  $\lambda_2 = \frac{E(R_1^*)}{\text{Var}(R_1^*)} \in (0, \infty)$  and

$$E(R_i^*) + \lambda_2 E(R_i^*) E(R_1^*) = \lambda_2 E(R_i^* R_1^*)$$

$i=1, \dots, [n/2]$  the last expression can be rewritten as  $E(R_i^*) = \lambda_1 E(R_i^* R_1^*)$ ,

$i=1, \dots, [n/2]$  with  $\lambda_1 = \frac{\lambda_2}{1 + \lambda_2 E(R_1^*)}$  which is (ii). There fore all conditions (i)-

(iv) are equivalent.

Assume now that (i) holds. Then from (3.7), the BLIE of  $\sigma$  is

$L_I = \underline{M}' Q^{-1} \underline{R} = \lambda_1 (\underline{n}' \underline{R}) = \lambda_1 (X_{2:n} - X_{1:n} + X_{n:n} - X_{n-1:n})$  and the other formula follows from (3.9) and (3.4).

In order to prove the necessity, assume that  $L_\lambda = \lambda R_1 = \lambda (\underline{n}' \underline{R})$  is the BLIE of  $\sigma$ . Then  $E(\lambda R_1 - \sigma)^2 = \lambda^2 (\underline{n}' Q \underline{n}) + 1 - \lambda (\underline{n}' \underline{M}) \sigma^2$ , must be minimum with

respect to  $\lambda$ , showing that  $\lambda = \frac{\underline{n}' \underline{M}}{\underline{n}' Q \underline{n}}$ . Since for this value of  $\lambda$  we must have

$$E(\lambda R_1 - \sigma)^2 = \left( 1 - \frac{(\underline{n}' \underline{M})^2}{\underline{n}' Q \underline{n}} \right) \sigma^2 = \text{MSE}(L_I) = (1 - \underline{M}' Q^{-1} \underline{M})^2, \text{ we conclude}$$

that  $(\underline{n}' \underline{M})^2 = (\underline{n}' Q \underline{n})(\underline{M}' Q^{-1} \underline{M})$ . This is Cauchy-Schwarz inequality written as an equality and, therefore, this equality is attained only if there exist a constant  $\lambda_1$  such that  $\underline{M} = \lambda_1 (Q \underline{n})$ , completing the proof.

The non-negativity nature of the estimator  $L_u$  and  $L_I$  of the common scale parameter  $\sigma$  is given in the following theorem.



**Theorem 4.2:** If either  $n=2$  or  $3$  then the *BLUE* (and the *BLIE*) of the common scale parameter  $\sigma$  is nonnegative.

**Proof:** If  $n=2$  or  $3$ , then by theorem 4.1 the  $n=2$  or  $3$  of  $\sigma$  is a constant multiple of the pooled sample range and the result is obvious.

**Theorem 4.3:** If the known distribution functions,  $F_i(y), i=1,2,\dots,k$  are such that

$$\text{Cov}(R_i^* R_j^*) \leq 0, \quad i \neq j, \quad i, j=1,\dots,[n/2] \quad (4.1)$$

then the *BLUE* (and the *BLIE*) of the common scale parameter  $\sigma$  is non-negative.

**Proof:** Under (4.1) the positive definite matrix  $H$  has non-positive off-diagonal elements. Therefore from theorem 12.2.9 in Graybill(1969) it follows that the

positive definite matrix  $H^{-1}$  has all its elements non-negative, this shows that  $H^{-1}M > 0$  component wise, and the assertion follows from expression (3.4).

## 5. ESTIMATION OF COMMON SCALE PARAMETER OF NORMAL AND DOUBLE EXPONENTIAL DISTRIBUTIONS

In this section we consider a random sample of size  $n_1$  drawn from a normal distribution with probability density function

$$f_1(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \quad -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0$$

and sample of size  $n_2$  drawn from double exponential distribution with probability density function

$$f_2(x, \mu, \sigma) = \frac{1}{\sqrt{2}\sigma} e^{-\sqrt{2}\left|\frac{x-\mu}{\sigma}\right|}, \quad -\infty < x < \infty \text{ for } 1 \leq n_1 \leq 5, 1 \leq n_2 \leq 5$$

and illustrate the method proposed in section 3 to estimate the common scale parameter  $\sigma$  of the above two distributions by function of spacings of pooled sample of observations. To obtain the estimators we have evaluated means, variance and co variances of function of spacings of the combined sample, by using the means, variances and covariances of order statistics of the combined sample consisting of observations drawn from standard normal distribution with probability density function  $f_1(x,0,1)$  and standard double exponential distribution with probability density function  $f_2(x,0,1)$  for  $n=2(1)5$  given in sajeevkumar and Thomas(2005), and are presented in Table 1.

The coefficients  $c_1, c_2, \dots, c_{[n/2]}$  of the BLUE  $L_u = \sum_{i=1}^{[n/2]} c_i R_i$ , ( $Var(L_u)$ ) and the coefficients  $d_1, d_2, \dots, d_{[n/2]}$  of the BLIE  $L_l = \sum_{i=1}^{[n/2]} d_i R_i$ , ( $MSE(L_l)$ ) have been also evaluated and are presented in Table 2. From Table 1, it is noted that all  $Cov(R_i^*, R_j^*) \leq 0$ , for  $i \neq j$  and hence the BLUE and BLIE for  $\sigma$  is positive, which is evident in Table 2.

**Table 1:** Expected value, Variances and co-variances of function of spacings arising from Standard normal and double exponential distributions.

Sample size (n)	$n_1$	$n_2$	Choice of $i$ for $1 \leq i \leq [n/2]$	$E(R_i^*)$	Choice of $i, j$ for $1 \leq i \leq j \leq [n/2]$	$Cov(R_i^*, R_j^*)$
2	1	1	1	2.20048	1,1	3.15720
3	1	2	1	1.63056	1,1	0.98402
	2	1	1	1.66422	1,1	0.88264
4	1	3	1	1.47626	1,1	0.92948
			2	1.02692	1,2	-0.04464
					2,2	0.84008
	2	2	1	1.47550	1,1	0.83992
			2	1.08172	1,2	-0.07628
					2,2	0.88256
3	1	1	1.47148	1,1	0.75402	
		2	1.13568	1,2	-0.11012	
				2,2	0.93376	
5	1	4	1	1.42118	1,1	0.91860
			2	0.84668	1,2	-0.01894
					2,2	0.29218
	2	3	1	1.40312	1,1	0.83306
			2	0.88320	1,2	-0.03396
					2,2	0.29750
	3	2	1	1.38264	1,1	0.75080
			2	0.91944	1,2	-0.04996
					2,2	0.30422
	4	1	1	1.36010	1,1	0.67176
2			0.95514	1,2	-0.06730	
				2,2	0.31268	

**Table 2:** Coefficients of the functions of spacings in the BLUE  $L_U$  and BLIE  $L_I$  of  $\sigma$ ,  $\sigma^{-2}Var(L_U)$  and  $\sigma^{-2}MSE(L_I)$ .

Sample Size (n)	$n_1$	$n_2$	Estimators	$L_U = \sum_{i=1}^{[n/2]} c_i R_i / L_I = \sum_{i=1}^{[n/2]} d_i R_i$		$\sigma^{-2}Var(L_U)$ $\sigma^{-2}MSE(L_I)$
				$c_1 / d_1$	$c_2 / d_2$	
2	1	1	$L_U$	0.45445.		0.65203
			$L_I$	0.60532		0.39468
3	1	2	$L_U$	0.61329		0.37011
			$L_I$	0.70110		0.72987
	2	1	$L_U$	0.60088		0.31869
			$L_I$	0.75833		0.24167
4	1	3	$L_U$	0.43648	0.34633	0.26434
			$L_I$	0.34522	0.27392	0.20907
	2	2	$L_U$	0.43991	0.32440	0.23365
			$L_I$	0.35660	0.26296	0.18940
	3	1	$L_U$	0.44583	0.30287	0.20579
			$L_I$	0.36974	0.25118	0.17067
5	1	4	$L_U$	0.33323	0.62174	0.20710
			$L_I$	0.27606	0.51507	0.17157
	2	3	$L_U$	0.33903	0.59363	0.18692
			$L_I$	0.28564	0.50014	0.15749
	3	2	$L_U$	0.34732	0.56532	0.16818
			$L_I$	0.29732	0.48393	0.14397
	4	1	$L_U$	0.35836	0.53667	0.15044
			$L_I$	0.31150	0.46650	0.13077

**Remark:** To compare the efficiency of our estimator  $L_U$  we can take the BLUE  $\sigma^* = \delta U_1 + (1 - \delta)U_2$  of  $\sigma$  based on  $U_1$  and  $U_2$ , where  $U_1$  is the Lloyd's BLUE of  $\sigma$  based on a sample of size  $n_1$  arising from normal distribution alone and  $U_2$  is the Lloyd's BLUE of  $\sigma$  based on a sample of size  $n_2$  arising from double exponential distribution alone. Here again  $\sigma^*$  is the BLUE based on  $U_1$  and  $U_2$ , when  $\delta = \frac{Var(U_2)}{Var(U_1) + Var(U_2)}$ . The efficiency

comparison of  $L_U$  relative to  $\sigma^*$  for  $n = 2(1)5, n_1, n_2 < 5, n_1 + n_2 = 5$  are given in Sajeev Kumar and Thomas(2005). From Sajeev Kumar and Thomas (2005) it is clear that  $Var(L_U)$  is much less than variance of  $\sigma^*$ .

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### REFERENCES

- Arnold, B. C., Balakrishnan, N. Nagaraja, H. N. (1992): *A First Course in Order Statistics*, Wiley, New York.
- Balakrishnan, N., Cohen, A. C. (1991): *Order Statistics and Inference: Estimation Methods*, Academic Press: San Diego.
- Balakrishnan, N., Papadatos, N. (2002): The use of spacings in the estimation of a scale parameter. *Statist. Probab. Lett.* **57**, 193-204.
- Bapat, R. B. and Beg, M. I. (1989): Order statistics for non identically distributed variables and permanents. *Sankhya A*, **51**, 79-93.
- David, H. A., Nagaraja, H. N. (2003): *Order Statistics*, 3<sup>rd</sup> ed. John Wiley and Sons, New York.
- Gray bill, F.A. (1969): *Introduction to Matrices and Applications in Statistics*. Wadsworth, Belmont, CA.
- Sajeevkumar, N. K. and Thomas, P. Y. (2005): Applications of order statistics of independent and non identically distributed random variables in estimation. *Comm. Statist. Theory and Methods*, **34**, 775-783.
- Sajeevkumar, N. K. and Thomas. P.Y. (2010): Use of spacings in the estimation of common scale parameter of several distributions. *Comm. Statist. Theory. and Methods*, **39**, 1951-1959.

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R.S.Priya and P.Yageen Thomas  
Department of Statistics  
Univerity of Kerala  
Trivandrum - 695 581  
India

Email: rsriyathoppil@gmail.com  
yageenthomas@gmail.com