UNIT 10 RANDOMISED BLOCK DESIGN

Structure

10.1 INTRODUCTION

The completely randomised design was simple due to the reason that principle of local control was not used and it was assumed that the experimental material is homogeneous, but it is observed that the experimental material is not fully homogeneous. In agricultural field experiments sometimes a fertility gradient is present in one direction. In such situation the simple method of controlling variability of the experimental material consist in stratifying or grouping the whole experimental area into relatively homogeneous strata or sub-groups (called blocks), perpendicular to the direction of fertility gradient. These blocks are so formed that plots within a block are homogeneous and between blocks are heterogeneous. In other words, there may be less variation within a block and major difference or variation between blocks. It is to be kept in mind that familiarity with the nature of experimental units is necessary for an effective blocking of the material. The procedure of division of experimental material into a number of blocks give rise to a design known as Randomised block design (RBD) which can be defined as an arrangement of t treatments in r blocks such that each treatment occurs precisely once in each block.

In other words, when the experimental units are heterogeneous, a part of the variability can be accounted for by grouping the experimental units in such a way that those experimental units within each group are as homogeneous as possible. The treatments are then allotted randomly to the experimental units within each group (or block). This results in an increase in precision of estimates of the treatment contrasts, due to the fact that error variance that is a function of comparisons within blocks is smaller because of homogeneous blocks.

Layout and statistical analysis of randomised block design are explained in Sections 10.2 and 10.3. The least square estimates of effects, variance of the estimates and expectation of sum of squares are also given in Section 10.3.

Missing plots techniques in RBD for one and two missing plots are described in Section 10.4 whereas the suitability of RBD is explored in Section 10.5.

Objectives

After studying this unit, you would be able to

- explain the randomised block design;
- describe the layout of RBD;
- explain the statistical analysis of RBD;
- find out the missing plots in RBD; and
- explain the advantages and disadvantages as well as the suitability of RBD.

10.2 LAYOUT OF RANDOMISED BLOCK DESIGN

The entire experimental material is divided into a number of blocks equal to the number of replications for each treatment. Then each block is divided into a number of plots equal to the number of treatments. For example if we have 4 treatments A, B, C and D and each treatment is to be replicated 3 times. Then according to the condition of RBD, we will arrange the experimental material in three blocks each of size 4, i.e. each block consists of 4 plots. After arranging the experimental material into a number of blocks, treatments are allocated to each block separately. That is randomisation is applied afresh for each block and thus, it will be independent for each block. The method is illustrated below by the following arrangement of 3 blocks and 4 treatments:

Layout of RBD with 4 treatments

Block I	A	B	D	C
Block II	C	A	D	B
Block III	D	B	C	A

10.3 STATISTICAL ANALYSIS OF RBD

If in RBD a single observation is made on each of the experimental units, then its analysis is analogous to ANOVA for fixed effect model for a two-way classified data with one observation per cell and the linear model effects to be (additive) becomes

$$y_{ij} = \mu + \alpha_i + \beta_j + e_{ij}\ ; \qquad i = 1, 2, \ldots, p;\ j = 1, 2, \ldots, q.$$

where, y_{ij} is the yield or response of the experimental unit receiving the i^{th} treatment in the j^{th} block, μ is the general mean effect, α_i is the effect due to the i^{th} treatment, β_j is the effect due to j^{th} block or replicate and e_{ij} is identically and independently distributed i.e. e_{ij} follows (i.i.d.) $N(0, \sigma_e^2)$, where μ, α_i and β_j are constants so that $\sum_{i=1}^{p}\alpha_i = 0$ and $\sum_{j=1}^{q}\beta_j = 0$.

If we write that

$$\sum_i \sum_j y_{ij} = y_{..} = G = \text{Grand total of all the } p \times q \text{ observations.}$$

$$\sum_j y_{ij} = y_{i.} = \alpha_i = \text{Total for } i^{th} \text{ treatment}$$

$$\sum_i y_{ij} = y_{.j} = \beta_j = \text{Total for } j^{th} \text{ block}$$

Then heuristically, we get

$$\sum_i \sum_j (y_{ij} - \bar{y}_{..})^2 = \sum_i \sum_j [(\bar{y}_{i.} - \bar{y}_{..}) + (\bar{y}_{.j} - \bar{y}_{..}) + (y_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..})]^2$$

$$= q\sum_i (\bar{y}_{i.} - \bar{y}_{..})^2 + p\sum_j (\bar{y}_{.j} - \bar{y}_{..})^2 + \sum_i \sum_j (y_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..})^2$$

The product terms vanish since the algebraic sum of deviations from mean is zero. Thus

TSS = SSE + SSB + SST

where TSS, SST, SSB and SSE are the total sum of squares, sum of squares due to treatments (between treatments SS), sum of squares due to blocks and sum of squares due to error (i.e., within treatment SS) given respectively by

$$\text{TSS} = \sum_i \sum_j (y_{ij} - \bar{y}_{..})^2$$

$$\text{SST} = q\sum_i (\bar{y}_{i.} - \bar{y}_{..})^2 = S_T^2 \text{ (say)}$$

$$\text{SSB} = p\sum_j (\bar{y}_{.j} - \bar{y}_{..})^2 = S_B^2$$

$$\text{SSE} = S_E^2 = \text{TSS} - \text{SSB} - \text{SST}$$

Hence, the total sum of squares is partitioned into three sum of squares whose degree of freedom make the total to the degree of freedom of TSS.

ANOVA Table for RBD

Source of Variation	**DF**	**SS**	**MSS**	**Variance Ratio(F)**
Treatments	$p-1$	S_T^2	MSST= $S_T^2/(p-1)$	$F_T = \frac{MSST}{MSSE}$
Blocks	$q-1$	S_B^2	MSSB = $S_B^2/(q-1)$	$F_B = \frac{MSSB}{MSSE}$
Error	$(p-1)(q-1)$	S_E^2	MSSE = $S_E^2/(p-1)(q-1)$	
Total	$pq-1$			

Under the null hypothesis, $H_0: \alpha_1 = \alpha_2 = \ldots = \alpha_p$ against the alternative that all α's are not equal, the test statistic

$$F_T = \frac{MSST}{MSSE} \quad \text{follows } F\,[(p-1), (p-1)(q-1)]$$

i.e., F_T follows F-distribution with $[(p-1), (p-1)(q-1)]$ df.

If $F_T \geq F$ with $[(p-1), (p-1)(q-1)]$ df at α level of significance, (Usually 5%) then H_0 is rejected and we conclude that treatments differ significantly.

If $F_T < F$ with $[(p-1), (p-1)(q-1)]$ df at α level of significance then H_0 may be accepted, i.e. the data do not provide any evidence against the null hypothesis which may be accepted.

Similarly, under the null hypothesis, $H_0: \beta_1 = \beta_2 = \ldots = \beta_q$ against the alternative that all β's are not equal, the test statistic

$$F_T = \frac{MSSB}{MSSE} \quad \text{follows } F[(q-1), (p-1)(q-1)]$$

and we can discuss its significance as explained above.

10.3.1 Least Square Estimates of Effects

Proceeding exactly similar as in CRD, and replacing k by p, n by q and taking N = pq, the estimates of the parameters μ, α_i and β_j are given by:

$$\hat{\mu} = \bar{y}_{..},\ \hat{\alpha}_i = \bar{y}_{i.} - \bar{y}_{..},\ \hat{\beta}_j = \bar{y}_{.j} - \bar{y}_{..} \qquad \ldots (1)$$

10.3.2 Variance of the Estimates

Proceeding exactly similar as in CRD, we shall get

$$\text{Var}\,(\hat{\mu}) = \frac{\sigma_e^2}{pq}$$

$$\text{Var}\,(\hat{\alpha}_i) = \frac{(p-1)}{pq}\sigma_e^2$$

and $$\text{Var}(\hat{\beta}_j) = \frac{(q-1)}{pq}\sigma_e^2 .$$

10.3.3 Expectation of Sum of Squares

Proceeding exactly as in CRD, we get

$$E[SST] = (p-1)\sigma_e^2 + q\sum_i \alpha_i^2$$

$$E\left[\frac{(SST)}{(p-1)}\right] = E(MSST) = \sigma_e^2 + \frac{q}{(p-1)}\sum_i \alpha_i^2$$

$$E(SSB) = (q-1)\sigma_e^2 + p\sum_j \beta_j^2$$

$$E\left[\frac{(SSB)}{(q-1)}\right] = E(MSSB) = \sigma_e^2 + \frac{p}{(q-1)}\sum_j \beta_j^2$$

$$E(SSE) = (q-1)(p-1)\sigma_e^2$$

$$E\left[\frac{(SSE)}{(q-1)(p-1)}\right] = E(MSSE) = \sigma_e^2$$

Hence under the null hypothesis

$$H_{0\alpha} : \alpha_1 = \alpha_2 = \ldots. = \alpha_p = 0;$$

$$H_{0\beta} : \beta_1 = \beta_2 = \ldots. = \beta_q = 0$$

$$E\ (MSST) = \sigma_e^2 \text{ and } E(MSSB)\ = \sigma_e^2$$

i.e. each of the mean sum of squares due to treatments and blocks gives an unbiased estimate of the error variance σ_e^2 under the null hypothesis $H_{0\alpha}$ and $H_{0\beta}$ respectively.

Example 1: There were 4 different makes of cars. A problem was posed to estimate the petrol consumption rates of the different makes of cars for suitable average speed and compare them. The following experiment could be conducted for an inference about the problem:

Five different cars of each four makes were chosen at random. The five cars of each make were put on road on 5 different days. The cars of A make run with different speeds on different days. The speeds were 25, 35, 50, 60 and 70 mph. Which car was to put on the road on which day and what speed it should have was determined through a chance mechanism subject to the above conditions of the experiment. The procedure was adopted for each of the makes of cars. For each car, the number of miles covered per gallon of petrol was observed. The observations are presented below:

Table: Miles per Gallon of Petrol

Makes of Car	**Speed of the cars in miles per hour (mph)**						**Average**
	25	35	50	60	70	Total	
A	20.6	19.5	18.1	17.9	16.0	92.1	18.42
B	19.5	19.0	15.6	16.7	14.1	84.9	16.98
C	20.5	18.5	16.3	15.2	13.7	84.2	16.84
D	16.2	16.5	15.7	14.8	12.7	75.9	15.18
Total	76.8	73.5	65.7	64.6	56.5	337.1	

Carry out the analysis of the given RBD.

Solution: Here the makes of the cars are the treatments and the other controlled factor is the speed, the variance for which has been eliminated through the design which is thus actually a randomised block design with the speeds as blocks. The specific cars used, the effects of the days, drivers and possibly some other effects contributed to the error variance.

Here,

Correction Factor (CF) = $\dfrac{(337.1)^2}{20} = 5681.82$

Raw Sum of Squares = $(20.6)^2 + (19.5)^2 + ... + (13.7)^2 + (12.7)^2$ = 5781.41

Total Sum of Squares (TSS) = 5681.41 - 5681.82 = 99.59

Sum of Squares due to Speed (SSS)

$$= \frac{(76.8)^2 + (73.5)^2 + ... + (64.6)^2 + (56.5)^2}{4} - CF$$

= 66.04

Sum of Squares due to Makes (SSM)

$$= \frac{(92.1)^2 + (84.9)^2 + (84.2)^2 + (75.9)^2}{5} - CF$$

= 28.78

Sum of Squares due to Errors (SSE)

= TSS − SSS − SSM

= 99.59 − 66.04 − 28.78 = 4.77

Analysis of Variance Table

Source of Variation	DF	SS	MSS	Variance Ratio	
				Calculated	**Tabulated**
Speeds	4	66.04	16.57	41.27	3.26
Treatments (Makes)	3	28.78	9.59	23.97	3.49
Error	12	4.77	0.40		
Total	19	99.59			

In both the cases either for speeds or for makes, calculated value of F is greater than tabulated value of F at 5% level of significance and thus null hypothesis is rejected.

In the above experiment, we are interested only on makes so multiple camparison test will be applied for different makes.

Mean number of miles per gallon for different Makes

	Makes		
$\bar{A}$	$\bar{B}$	$\bar{C}$	$\bar{D}$
18.42	16.98	16.84	15.18

$$SE = \sqrt{\frac{2MSSE}{5}} = \sqrt{\frac{2 \times 0.40}{5}} = 0.40$$

Critical difference at 1 % level of significance

$$CD = t_{\alpha/2} \text{ (for error df)} \times SE = 3.055 \times 0.40 = 1.22$$

The initial difference indicates that the Make A is significantly better than all the other Makes.

Pair of Treatments	**Difference**	**CD**	**Inference**
A, B	$\lvert\bar{A} - \bar{B}\rvert = 1.44$	1.22	Significant
A, C	$\lvert\bar{A} - \bar{C}\rvert = 1.58$	1.22	Significant
A, D	$\lvert\bar{A} - \bar{D}\rvert = 3.24$	1.22	Significant
B, C	$\lvert\bar{B} - \bar{C}\rvert = 0.14$	1.22	Insignificant
B, D	$\lvert\bar{B} - \bar{D}\rvert = 1.8$	1.22	Significant
C, D	$\lvert\bar{C} - \bar{D}\rvert = 1.66$	1.22	Significant

Example 2: Carryout the analysis of the following design:

Varieties	**Blocks**			
	I	**II**	**III**	**IV**
A	7	16	10	11
B	14	15	15	14
C	8	16	7	11

Solution: Let us find the block and variety totals by the following table:

Varieties	**Blocks**				**Total**
	I	**II**	**III**	**IV**	
A	7	16	10	11	44
B	14	15	15	14	58
C	8	16	7	11	102
Total	29	47	32	36	144

Correction Factor (CF) = $\frac{(144)^2}{12} = 1728$

Raw Sum of Squares (RSS) = $(7)^2 + (14)^2 + ... + (14)^2 + (11)^2$ = 1858

Total Sum of Squares (TSS) = 1858 − 1728 = 130

Block Sum of Squares (SSB) $= \dfrac{(29)^2 + (47)^2 + (32)^2 + (36)^2}{3} - CF$

$$= \frac{841 + 2209 + 1024 + 1296}{3} - 1728$$

$$= 1790 - 1728 = 62$$

Variety Sum of Squares (SSV) $= \dfrac{(44)^2 + (58)^2 + (42)^2}{4} - CF$

$$= \frac{1936 + 3364 + 1764}{4} - 1728$$

$$= 1766 - 1728 = 38$$

Sum of Squares due to Error (SSE) = TSS − SSV − SSB

= 130 − 62 −38 = 30

ANOVA Table

Source of Variation	DF	SS	MSS	Variance Ratio	
				Calculated	Tabulated
Variety	2	38	19	3.8	5.14
Blocks	3	62	20.67	4.13	4.76
Error	6	30	5		
Total	11	130			

In both these cases either for varieties or for blocks, calculated value of F is less than tabulated value of f at 5% level of significance and thus null hypothesis is accepted and inferred that variety effect and block effect are insignificant.

E1) Carryout the analysis of following design:

Blocks			
I	**II**	**III**	**IV**
A 8	**C** 10	**A** 6	**B** 10
C 12	**B** 8	**B** 9	**A** 8
B 10	**A** 8	**C** 10	**C** 9

10.4 MISSING PLOTS TECHNIQUE IN RBD

Sometimes observations from one or more experimental units are not found (missing) due to some unavoidable causes. There may be some unforeseen causes for example in agricultural experiments damage by animal or pets, in animal experiment any animal may die or observations from one or more plot is excessively large as compared to other plots and thus accuracy of such observation is often in doubt. In such situations, these observations are omitted and treated as missing.

In case of missing observations, analysis is done by estimating the missing observation. This type of analysis was given by Yates (1937) and it is known as missing plot technique.

10.4.1 One Missing Plot

Suppose without loss of generality that observation for treatment 1 in block 1 i.e. y_{11} is missing and let it is Y, then the observations for a RBD may be represented as below:

	T_1	T_2	…..	T_i	…	T_p	Total
B_1	$y_{11}=Y$	y_{21}	…	y_{i1}	…	y_{p1}	$B_1' + Y$
B_2	y_{12}	y_{22}	…	y_{i2}	…	y_{p2}	B_2
…	…	…	…	…	…	…	…
B_j	y_{1j}	y_{2j}	…	y_{ij}	…	y_{pj}	B_j
…	…	…	…	…	…	…	…
B_q	y_{1q}	y_{2q}	…	y_{iq}	…	y_{pq}	B_q
Total	$T_1' + Y$	T_2	….	T_i	…	T_p	$G' + Y$

where,

B_1' = total of all available $(p-1)$ observations in 1st block

T_1' = total of all available $(q-1)$ observations in 1st treatment.

G' = total of all available $(pq-1)$ observations

On the basis of these totals we calculate different SS's as follows:

$$\text{Sum of Squares for Blocks (SSB)} = \frac{(B_1' + Y)^2 + \sum_{j=2}^{q} B_j^2}{p} - \frac{(G'+Y)^2}{pq}$$

$$\text{Sum of Squares for Treatments (SST)} = \frac{(T_1' + Y)^2 + \sum_{i=2}^{p} T_i^2}{q} - \frac{(G'+Y)^2}{pq}$$

$$\text{Total Sum of Squares (TSS)} = \sum_i \sum_j y_{ij}^2 + Y^2 - \frac{(G'+Y)^2}{pq} \text{ where } (i,j) \neq (1,1)$$

Sum of Squares due to Error (SSE) = TSS – SSB – SST

$$\text{SSE} = Y^2 + \frac{(G'+Y)^2}{pq} - \frac{(B_1' + Y)^2}{p} - \frac{(T_1' + Y)^2}{q} + \text{terms not involving Y}$$

For obtaining the value of Y, we minimize the sum of squares due to error with respect to Y. This is obtained by solving the equation

$$\frac{\partial(SSE)}{\partial Y} = 2Y + \frac{2(G'+Y)}{qp} - \frac{2(B_1^{'} + Y)}{p} - \frac{2(T_1^{'} + Y)}{q} = 0$$

$$\Rightarrow Y + \frac{Y}{pq} - \frac{Y}{p} - \frac{Y}{q} = \frac{T_1^{'}}{q} + \frac{B_1^{'}}{p} - \frac{G'}{pq}$$

$$\Rightarrow \frac{Y(pq + 1 - q - p)}{pq} = \frac{pT_1^{'} + qB_1^{'} - G'}{pq}$$

$$\hat{Y} = \frac{pT_1^{'} + qB_1^{'} - G'}{(p-1)(q-1)}$$

$\hat{Y}$ is the least square estimate of the yield of the missing plot. The value of Y is inserted in the original table of yield and ANOVA is performed in the usual way except that for each missing observation 1 df is subtracted from total and consequently from error df.

10.4.2 Two Missing Plots

For two missing values, we convert the problem into one missing value by putting any value say the overall mean or mean of the available values of that block for which one value is missing or mean of the available values of that replicate in any missing cell and obtain the estimate of the second missing value by the above prescribed estimation formula. Then we put the estimate of this second missing value and estimate the first missing value for which originally mean was taken. We go on repeating the same procedure until we obtain two successive estimates which are not materially different. Method is illustrated below with examples.

Example 3: In the following data two values are missing. Estimate these values by Yates method and analyse:

Treatments	**Blocks**		
	I	**II**	**III**
A	12	14	12
B	10	y	8
C	x	15	10

Solution: We convert the two missing plots problems into one missing plot problem, for which we take the average of the values of I block in which x is missing. This average is (10+12)/2 = 11. Thus, the estimate of x is taken to be x_1=11 and it is inserted in place of x and form the following table of totals:

Treatments	**Blocks**			**Total**
	I	**II**	**III**	
A	12	14	12	$T_A = 38$
B	10	y	8	$T_B = 18 + y$
C	11	15	10	Tc = 36
Total	$B_1 = 33$	$B_2 = 29 + y$	$B_3 = 30$	G = 92 + y

Thus, from the above table we get

$$p = 3,\ q = 3,\ B_2^{'} = 29,\ T_B^{'} = 18,\ G^{'} = 92$$

Applying the missing estimation formula

$$\hat{Y} = \frac{pT_1^{'} + qB_1^{'} - G^{'}}{(q-1)(p-1)} = \frac{3\times 18 + 3\times 29 - 92}{4}$$

$$= \frac{54+87-92}{4} = \frac{49}{4} = 12.25 \approx 12$$

Now the estimated value of y is taken to be $y_1 = 12$ and it is inserted in place of y and the following table of totals is formed by taking x unknown:

Treatments	Blocks			Total
	I	II	III	
A	12	14	12	$T_A = 38$
B	10	12	8	$T_B = 30$
C	x	15	10	$T_c = 25 + x$
Total	$B_1 = 22+x$	$B_2 = 41$	$B_3 = 30$	$G = 93 + x$

Thus from the above table we get $p = 3,\ q = 3,\ B_1^{'} = 22,\ T_c^{'} = 25,\ G^{'} = 93$

Again applying the missing estimation formula

$$\hat{x} = \frac{3\times 25 + 3\times 22 - 93}{4}$$

$$= \frac{75+66-93}{4} = \frac{48}{4} = 12$$

Thus, $x_2 = 12$

Again using $x_2 = 12$, we estimate the second estimate of y i.e. y_2 for which

$$B_2^{'} = 29,\ T_B^{'} = 18,\ G^{'} = 92$$

$$\hat{y} = \frac{3\times 18 + 3\times 29 - 93}{4}$$

$$= \frac{54+87-93}{4} = \frac{47}{4} = 11.75 \approx 12$$

We see that the second estimate of y i.e. y_2 is not materially different from y_1.

Thus, we take the estimated values of $\hat{x} = 12$ and $\hat{y} = 12$. Inserting both the estimated values of x and y we get the following observations:

Treatments	Blocks			Total
	I	II	III	
A	12	14	12	$T_A = 38$
B	10	12	8	$T_B = 30$
C	12	15	10	$Tc = 37$
Total	$B_1 = 34$	$B_2 = 41$	$B_3 = 30$	$G = 105$

Correction Factor (CF) = $\frac{(105)^2}{9} = \frac{11025}{9} = 1225$

Raw Sum of Square (RSS) = $(12)^2 + (10)^2 + ... + (8)^2 + (10)^2$ = 1261

Total Sum of Squares (TSS) = 1261 - 1225 = 36

Treatment Sum of Squares (SST) = $\frac{(38)^2 + (30)^2 + (37)^2}{3} - \text{CF}$

$$= \frac{1444 + 900 + 1369}{3} - 1225$$

$$= \frac{3713}{3} - 1225 = 1237.67 - 1225$$

= 12.67

Block Sum of Squares (SSB) = $\frac{(34)^2 + (41)^2 + (30)^2}{3} - \text{CF}$

$$= \frac{1156 + 1681 + 900}{3} - 1225$$

$= 1245.67 - 1225$ = 20.67

Error Sum of Squares (SSE) = TSS − SST − SSB

= 36 − 12.67− 20.67 = 2.66

ANOVA Table

Source of Variation	DF	SS	MSS	Variance Ratio	
				Calculated	Tabulated
Treatments	3-1=2	12.67	6.34	4.77	9.55
Blocks	3-1=2	20.67	10.34	7.77	9.55
Error	4-2=2	2.66	1.33		
Total	8-2 =6				

In case of both treatments and blocks, calculated value of F is less than tabulated value of F at 5% level of significance, thus treatment and block means are not significantly different.

E2) For the given data the yield of the treatment C in 2^{nd} block is missing. Estimate the missing value and analyse the data:

Blocks	Treatments			
	A	B	C	D
I	105	114	108	109
II	112	113	Y	112
III	106	114	105	109

10.5 SUITABILITY OF RBD

1. The RBD is suitable in the situations where it is possible to divide the experimental material into a number of blocks. If it is not possible to divide the experimental material, RBD cannot be used.

2. The RBD is suitable only when the number of treatments is small because as the number of treatments increases, the block size also increases and it disturbs the homogeneity of the block.

3. RBD is suitable only when experimental material is heterogeneous with respect to one factor only. If there is two-way heterogeneity, LSD is used.

10.5.1 Advantages and Disadvantages of RBD

Advantages of RBD

The RBD has many advantages over other designs. Some of them are listed below:

1. It is a flexible design. It is applicable to moderate number of treatments. If extra replication is necessary for some treatment, this may be applied to more than one unit (but to the same number of units) per block.
2. Since all the three principles of design of experiments are used, the conclusions drawn from RBD are more valid and reliable.
3. If data from individual units be missing then, analysis can be done by estimating it.
4. This is the most popular design in view of its simplicity, flexibility and validity. No other design has been used so frequently as the RBD.
5. This design has been shown to be more efficient or accurate than CRD, for most types of experimental work. The elimination of block sum of squares from error sum of squares, usually results in a decrease of error sum of squares.
6. Analysis is simple and rapid.

Disadvantages of RBD

1. The main disadvantage of RBD is that if the blocks are not internally homogeneous, then a large error term will result. In field experiments, it is usually observed that as the number of treatments increases, the block size increases and so one has lesser control over error.
2. The number of replications for each treatment is same. If replication is not same, the only remedy is to adopt CRD.
3. It cannot control two sided variation of experimental material simultaneously. That is why, it is not recommended when experimental material contains considerable variability.

10.6 SUMMARY

In this unit, we have discussed:

1. The randomised block design;
2. The layout of RBD;
3. The statistical analysis of RBD;
4. The missing plot techniques in RBD; and
5. The advantages and disadvantages as well as the suitability of RBD.

10.7 SOLUTIONS/ ANSWERS

E1) The given design is solved by method of analysis of variance for two-way classified data. The computation results are given as follows:

Correction Factor (CF) = 972

Raw Sum of Squares (RSS) = 998

Total Sum of Squares (TSS) = 26

Block Sum of Squares (SSB) = 4.67

Treatment Sum of Squares (SST) = 15.5

Error Sum of Squares (SSE) = 5.83

ANOVA Table

Source of Variation	DF	SS	MSS	Variance Ratio	
				Calculated	Tabulated
Variety	2	15.5	7.7	7.94	5.14
Blocks	3	4.67	1.56	1.61	4.76
Error	6	5.83	0.97		
Total	11	26			

In case of variety, calculated value of F is greater than the tabulated value at F at 5% level of siginificance, so we reject the null hypothesis and conclude that the treatment effect is significant, while for blocks, it is not significant. For pairwise testing, we have to find the standard error of difference of two treatment means:

$$SE = \sqrt{\frac{2MSSE}{q}} = \sqrt{\frac{2 \times 0.97}{3}} = 0.80$$

Critical difference (CD) = SE $\times\, t_{\alpha/2}$ at error df

$$= 0.80 \times 2.447 = 1.96$$

Treatment means are

$$\bar{A} = \frac{30}{4} = 7.5, \qquad \bar{B} = \frac{37}{4} = 9.25 \qquad \bar{C} = \frac{41}{4} = 10.25$$

Pair of Treatments	Difference	CD	Inference
A, B	$\lvert\bar{A} - \bar{B}\rvert = 1.76$	1.96	Insignificant
A, C	$\lvert\bar{A} - \bar{C}\rvert = 2.75$	1.96	Significant
B, C	$\lvert\bar{B} - \bar{C}\rvert = 1.00$	1.96	Insignificant

E2) We have p = 3, q = 4, $B_3' = 213$, $T_2' = 337$, $G' = 1207$ and the value of $\hat{y} = 109$

Therefore,

Correction Factor = 144321.33

Raw Sum of Squares = 144442.00

Total Sum of Squares = 120.67

Treatment Sum of Squares = 76.67

Block Sum of Squares = 20.67

Error Sum of Squares = 23.33

ANOVA Table

Source of Variation	DF	SS	MSS	Variance Ratio	
				Calculated	Tabulated
Treatments	3 - 1 = 2	20.67	10.33	2.21	5.79
Blocks	4 - 1 = 3	76.67	25.55	5.48	5.41
Error	6 - 1 = 5	23.33	4.66		
Total	11 - 1=10	120.67			

Block means are not but treatment means are significantly different at 5% level of significance.

In the above experiment, we are interested only treatments, so multiple camparison test will be applied for different treatments.

For pairwise testing, we have to find the standard error of difference of two treatment means:

$$SE = \sqrt{\frac{2MSSE}{p}} = \sqrt{\frac{2 \times 4.66}{3}} = 1.76$$

$$CD = SE \times t_{\alpha/2} \text{ at error df}$$

$$= 1.76 \times 2.447 = 4.31$$

Treatment means are

$$\overline{A} = \frac{323}{3} = 107.67,\ \overline{B} = \frac{341}{3} = 113.67,\ \overline{C} = \frac{322}{3} = 107.33, \overline{D} = \frac{330}{3} = 110$$

Pair of Treatments	**Difference of Treatment Means**	**CD**	**Inference**
A, B	$\lvert\overline{A} - \overline{B}\rvert = 6.0$	4.31	Significant
A, C	$\lvert\overline{A} - \overline{C}\rvert = 0.3$	4.31	Insignificant
A, D	$\lvert\overline{A} - \overline{D}\rvert = 2.3$	4.31	Insignificant
B, C	$\lvert\overline{B} - \overline{C}\rvert = 6.3$	4.31	Significant
B, D	$\lvert\overline{B} - \overline{D}\rvert = 3.7$	4.31	Insignificant
C, D	$\lvert\overline{C} - \overline{D}\rvert = 2.7$	4.31	Insignificant