

Chapter 28

Balanced Incomplete Block Design

Block	BIBD product formulation				
	1	2	3	4	5
1	X	X	X		
2	X	X		X	
3	X	X			X
4	X		X	X	
5	X		X		X
6	X			X	X
7		X	X	X	
8		X	X		X
9		X		X	X
10			X	X	X

When the number of experimental units in each block is less than the number of treatment combinations

Balanced when every treatment appears w/ every other treatment in the same block the same number of times

• 1 & 2 appear together in 3 blocks

• 1 & 3

• 1 & 4

• 1 & 5

• ⋮

• 4 & 5

} Thus balanced

With $r = \#$ of treatments, $r_b = \text{block size}$, $n_b = \#$ of blocks and no restriction on n_b we can construct a BIBD by listing $\binom{r}{r_b}$ subsets of size r_b from all treatments

Advantages and Disadvantages

- 1) Helpful with studies that have a lot of treatments
- 2) Simplifies analysis
- 3) equal precision across groups
- 4) May waste collected data
- 5) Restrictive assumptions
- 6) More complex than RCBD

Model $Y_{ij} = \mu_{..} + \rho_i + \tau_j + \epsilon_{ij}$

- $\mu_{..}$ is a constant
- ρ_i are constants for the block row effects $\Rightarrow \sum \rho_i = 0$
- τ_j are constants for the treatment effects $\Rightarrow \sum \tau_j = 0$
- ϵ_{ij} are ind $N(0, \sigma^2)$
- no block-treatment interactions are present
- Sum of squares & tests are the same as the fixed effects model (Chapter 21)

Regression Approach $Y_{ij} = \mu_{..} + \rho_1 Z_{i1j} + \dots + \rho_9 Z_{i9j} + \tau_1 X_{i1j} + \dots + \tau_4 X_{i4j} + \epsilon_{ij}$

$\Rightarrow X_{ijk} = \begin{cases} 1 & \text{if from treatment } k \\ 0 & \text{otherwise} \end{cases}$

$Z_{ijk} = \begin{cases} 1 & \text{if from block } k \\ 0 & \text{otherwise} \end{cases}$

Tests

$R_1 \rightarrow Y_{ij} = \mu_{..} + \rho_1 Z_{i1j} + \dots + \rho_9 Z_{i9j} + \epsilon_{ij}$

$R_2 \rightarrow Y_{ij} = \mu_{..} + \tau_1 X_{i1j} + \dots + \tau_4 X_{i4j} + \epsilon_{ij}$

① $H_0: \tau_1 = \tau_2 = \tau_3 = \tau_4 = 0$

$H_a: \text{not } H_0$

$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \div MSE(F)$$

Reject if $F^* > F(1-\alpha, df_R, df_F)$

② $H_0: \rho_1 = \rho_2 = \dots = \rho_{10} = 0$

$H_a: \text{not } H_0$

$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \div MSE(F)$$

Reject if $F^* > F(1-\alpha, df_R, df_F)$

$$\hat{\mu}_{.j} = \hat{\mu}_{..} + \hat{\tau}_j$$

$$\sigma^2(\hat{L}) = \sigma^2\left(\sum_{j=1}^r c_j \hat{\mu}_{.j}\right) = \sigma \frac{n_b}{m_p} \sum_{j=1}^r c_j^2$$

- confidence intervals:
- $\hat{L} \pm \frac{1}{\sqrt{2}} q_{[1-\alpha, r, n_b n_b - n_b - r + 1]} s(\hat{L})$ pairwise-tukey
 - $\hat{L} \pm (r-1) F_{[1-\alpha, r-1, n_b n_b - n_b - r + 1]} s(\hat{L})$ Scheffe
 - $\hat{L} \pm t_{[1-\alpha/2g, n_b n_b - n_b - r + 1]}$ Bonferroni

SAS Look at chapter 21

Latin Square Designs • When it isn't feasible to use two blocking variables simultaneously in RCBD

Factor B	FACTOR A		
	1	2	3
1	T2	T1	T3
2	T1	T3	T2
3	T3	T2	T1

- There are r treatments and r levels in each block
- Each row and each column has all treatments
- No interactions
- Can have random blocks

Advantages

- 1.) Greater reduction in variability
- 2.) Good for pilot studies
- 3.) Keeps track of order

Disadvantages

- 1.) # of levels must = number of treatments
- 2.) Restrictive assumptions
- 3.) Very small degrees of freedom w/ few treatments
- 4.) large degrees of freedom w/ a lot of treatments

Model

$$y_{ijk} = \mu_{...} + \rho_i + \kappa_j + \tau_k + \epsilon_{ijk}$$

• $\mu_{...}$ is a constant

• ρ_i, κ_j, τ_k are constants $\Rightarrow \sum \rho_i = \sum \kappa_j = \sum \tau_k = 0$

• $\epsilon_{ijk} \sim N(0, \sigma^2)$

$$\begin{aligned}
 Y_{i..} &= \sum_j Y_{ijk} & \bar{Y}_{i..} &= \frac{Y_{i..}}{r} \\
 Y_{.j.} &= \sum_i Y_{ijk} & \bar{Y}_{.j.} &= \frac{Y_{.j.}}{r} \\
 Y_{..k} &= \sum_{i,j} Y_{ijk} & \bar{Y}_{..k} &= \frac{Y_{..k}}{r} \\
 Y_{...} &= \sum_i \sum_j Y_{ijk} & \bar{Y}_{...} &= \frac{Y_{...}}{r^2}
 \end{aligned}$$

$$\begin{aligned}
 \hat{\mu}_{...} &= \bar{Y}_{...} \\
 \hat{\beta}_i &= \bar{Y}_{i..} - \bar{Y}_{...} \\
 \hat{\kappa}_j &= \bar{Y}_{.j.} - \bar{Y}_{...} \\
 \hat{\tau}_k &= \bar{Y}_{..k} - \bar{Y}_{...} \\
 \hat{Y}_{ijk} &= \bar{Y}_{i..} + \bar{Y}_{.j.} + \bar{Y}_{..k} - 2\bar{Y}_{...} \\
 e_{ijk} &= Y_{ijk} - \hat{Y}_{ijk} = Y_{ijk} - \bar{Y}_{i..} - \bar{Y}_{.j.} - \bar{Y}_{..k} + 2\bar{Y}_{...}
 \end{aligned}$$

Sum of squares & Mean Squares Table 28.5 p 1189

Test ① H_0 : all $\tau_k = 0$

H_a : not H_0

$$F^* = \frac{MSTR}{MSRem}$$

Reject if $F^* > F[1-\alpha, r-1, (r-1)(r-2)]$

② H_0 : all row blocking variables = 0

H_a : not H_0

$$F^* = \frac{MSRow}{MSRem}$$

③ H_0 : all column blocking variables = 0

H_a : not H_0

$$F^* = \frac{MSCol}{MSRem}$$

• $s(\hat{\mu}) = \frac{2MSRem}{r}$

- Confidence Intervals :
- $\hat{\mu} \pm t[1-\alpha/2, (r-1)(r-2)]$
 - $\hat{\mu} \pm \frac{1}{2} q[1-\alpha, r, (r-1)(r-2)]$
 - $\hat{\mu} \pm (r-1) F[1-\alpha, r-1, (r-1)(r-2)]$
 - $\hat{\mu} \pm t[1-\alpha/2g, (r-1)(r-2)]$

- Diagnostics
- Look at Y_{ij} vs pred
 - Look at Y_{ij} vs blocks
 - Look at normal probability plot

• Power of F test $\phi = \frac{1}{\sigma} \sqrt{\sum \tau_k^2}$

• Efficiency of Blocking

$E_1 = \sigma_r^2 / \sigma_L^2$	$\hat{E}_1 = \frac{MSRow + MSCol + (r-1)MSRem}{(r+1)MSRem}$
$E_2 = \sigma_b^2 / \sigma_L^2$	$\hat{E}_2 = \frac{MSCol + (r-1)MSRem}{rMSRem}$
$E_3 = \sigma_c^2 / \sigma_L^2$	$\hat{E}_3 = \frac{MSRow + (r-1)MSRem}{rMSRem}$

Model w/ Replications within Cells

$Y_{ijk...m} = \mu_{...} + \rho_i + \kappa_j + \tau_k + \epsilon_{ijk...m}$

- $\mu_{...}$ is a constant
- ρ_i, κ_j, τ_k are constants $\Rightarrow \sum \rho_i = \sum \kappa_j = \sum \tau_k = 0$
- $\epsilon_{ijk...m} \sim N(0, \sigma^2)$

Sum of squares & Mean squares table 28.7 p 1196

skip 28.8

SAS /*To find the sample size necessary to get 80% Power*/

```
proc power;  
  onewayanova;  
  group means  $\mu_1$  |  $\mu_2$  |  $\mu_3$  |  $\mu_4$ ;  
  stddev =  $\sigma$ ;  
  alpha =  $\alpha$ ;  
  npergroup = .  
  power = .8;
```

run;

/* Latin Squares */

```
proc glm plots=all;  
  class A B Treatments;  
  model Y = A B Treatments;  
  ls means treatment / pdiff adjust=Tukey alpha=.05 cl;
```

run;