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Effectiveness of Split-Plot Design over Randomized Complete Block Design in Some Experiments

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ABSTRACT
One of the main features that distinguish split-plot experiments from other experiments is that they involve two types of experimental errors; the whole plot (WP) error and the split-plot (SP) error. This research paper compared the effectiveness of split-plot design (SPD) over randomized complete block design (RCBD). The data used for comparison is a 2^1 x 5^2 split-plot experiment with three replicates. It is been carried out to evaluate the threshing efficiency of an improved sorghum thresher; the three factors considered in the experiment are the feed at two different rates, moisture content at five different levels and speed at five different rates. The data is analyzed as split-plot and as randomized complete block design and their ANOVA results and relative efficiency (RE) statistic values were compared. The result reveals the effectiveness of split-plot design over randomized complete block design.
Key words: SPD, SP error, WP error, RCBD, Relative Efficiency

1. INTRODUCTION

Experiments performed by investigators in virtually all field of inquiry, are usually, to discover something about a particular process or system. Literally, an experiment is a test (Montgomery, 2005). The choice of experimental unit has been one of the signifying problems for various types of experiments. In field experiments the size and shape of plot and the size and shape of block are of great influence and the choice on these matters are of two types: statistical and others. Under statistical considerations we include topics such as effect of size and shape of plot on error variance and accuracy of estimation while the non-statistical considerations include such matters as the feasibility of particular sizes and shapes of plot from the point of view of experimentation.

Most field (agronomic) experiments are large and the choice of a suitable experimental unit may have some scope of ingenuity. The experimenter have to make the division of the experimental material into blocks in such a way that the plots within blocks are as homogeneous as possible, that is, block should remove as much trends in the material as possible. Kempthorne (1952) stated that if an inappropriate design for an experiment is used it faces considerable defects and it may not be easy to find a reasonably homogeneous area of dimensions of the experiment. In addition, column effects at one end of the experiment may be very different from column effects at the other end and such an effect would result in lower efficiency.

Cox (1958) stated that in a randomized complete block design (RCBD) the effects of certain sources of variation reduced by grouping the experimental units or by the use of adjustments based on a concomitant variable, the remaining variation convert into effective random variation by randomization. He further discussed, an agricultural field trials in the form of factorial experiments arranged in randomized complete block design the treatments must not be too large if these design is to be effective: often the number of treatments needs to be less than 20 for randomized complete block design, and sometimes the limit is lower than this. When the numbers of treatments exceed this limit, the blocks or rows and columns tend to become too heterogeneous resulting in a high residual standard deviation. He concluded that the grouping of the material into blocks eliminates the effect of constant differences between blocks and the randomization allows us to treat the remaining variation between units as random variation, so far as assessing treatment comparisons is concerned. The success of the randomized complete block design depends on a good grouping of the units into blocks, and the general idea of grouping into blocks is of fundamental importance and is not only frequently used in simple experiments but also forms the basis for most of the more complicated designs.

Cox (1958) again argued that the use of split-plot design is necessarily not when the whole plot treatments are likely to be compared with less precision than the subplot treatments because the whole plot treatments need not be restricted to a single factor but may consist of all combinations of the levels of several factors. He stated that the split-plot principle is applied to experiments on processes in which there are several stages and it may then be convenient to work with large batches of material at the first stage, dividing into smaller batches for the application of the treatment at the second stage.

Cochran and Cox (1956) stated that the chief practical advantage of the split-plot arrangement is, it enables factors that require relatively large amount of materials and factors that require only small amount of materials to be used. In addition, factors of second type can often be included at very little extra cost, and some additional information obtained very cheaply. They summarized that , the split-plot design is advantageous if the sub-plot (B) treatment and the interaction of the whole plot (A) and sub-plot (B) treatment effects are of greater interest than the whole plot treatment (A) effect, or if the whole plot (A) effect cannot be tested on small amount of materials. They gave two disadvantages mentioned by experimenters, which are; sometimes the whole-unit error is much larger than the sub-unit error. It may occur at times that the effect of whole-plot (A), though large and exciting, is not significant, whereas that of sub-plot (B), which is too small to be of practical interest, is statistically significant. The experimenter tends to be uncomfortable in reporting results of this type. Secondly, the fact that different treatment comparisons have different basic error variances makes the analysis more complex than with randomized complete block design, especially if some unusual type of comparison is being made. They commended that the split-plot Latin square eliminates error variation, which arise from two types of grouping, and is preferable to randomized complete block design (RCBD). They cited an example presented by Yates (1935) where he summarized 22 field experiments in Latin squares where the plots were split into halves, he found a substantial net increase in precision over randomized complete block design, and the superiority was so pronounced that even the whole-plot comparisons would have been less precisely determined in randomized complete block design.

Montgomery (2005) stated that the incorrect testing of effects for running an experiment in a completely randomized fashion instead of the split-plot design is because the error associated with the hard-to-change factor inflates the variance of the regression coefficient for the easily changed factor. Jones and Nachtcheim (2009) stated that when an industrial experiment, is prescribed wrongly it lead to incorrect analysis, which inflates the Type I, error rate for whole plot sub factors, as does the Type II error rate for split plot sub factors and whole plot by split-plot interactions. Therefore, one way to avoid these mistakes is to plan the experiment as a split-plot design in the first place. Not only does this avoid mistakes, it also leverages the economic and statistical efficiencies. Besides the less expensiveness of running the split-plot design, it is often a more statistically efficient design compared to other experimental designs because it handles large data with less error. Bisgaard *et al.* (1996) discussed this issue and stated that if a split-plot experiment is wrongly analyzed as a completely randomized experiment, some factors may be declared significant when they are not and vice versa.

Kowalski and Potcner (2003) stated that when a designed experiment uses blocks such as days or batches, the analysis of the experiment includes a term for these blocks. When a designed experiment is performed by fixing a factor and then running the combinations of the other factors, using different sized experimental units or using a different randomization for the factors (a split-plot design), the analysis should incorporate these features. They analyzed 23 factorial treatments design with two replicates using the split-plot approach. The responses were first analyzed incorrectly as if they came from a completely randomized design and then ran correctly as a split-plot design. It was observed that some treatment effects were declared significant for the completely randomized design and not for the split-plot design and vice versa. They stated that the cause is, in the completely randomized design, all factors effect use the mean square error as the estimate of experimental error. In a split-plot experiment, however, there are two different experimental error structures: one for the WP factor and one for the SP factor. They concluded that it is because of the two separate randomizations that occur when running the experiment.

2. MATERIALS AND METHODS

A $2^1 \times 5^2$ split-plot experiment with three replicates was carried out to evaluate the threshing efficiency of an improved sorghum thresher. The three factors considered in the experiment are the feed (whole plot factor) at two different rates, moisture content (first sub-plot factor) at five different levels and speed (second sub-plot factor) at five different rates. The data will be analyzed as split-plot design and as randomized complete block design, this is to check the effectiveness of the split-plot design over randomized complete block design. Their respective models are as follows;

2.1 Split-Plot Design Model

The model is a linear additive model, it is given as;

$$Y_{ijkl} = \mu + \alpha_i + \gamma_k + \ell_{ik} + \beta_j + \eta_l + (\alpha\beta)_{ij} + (\alpha\eta)_{il} + (\beta\eta)_{jl} + \ell_{ijkl} \text{ .... } (1)$$

where: Y_{ijkl} is the response; μ is a constant; α_i is the WP factor; γ_k is the block effect; ℓ_{ik} is the WP error, NID ~ $(0, \sigma^2)$; β_j is the first SP factor; η_l is the second SP factor; $(\alpha\beta)_{ij}$, $(\alpha\eta)_{il}$, $(\beta\eta)_{jl}$ are the interaction factors; ℓ_{ijkl} is the SP error, NID ~ $(0, \sigma^2)$; i = 1, 2, 3, …, a (levels of WP factor), j = 1, 2, 3, …, b (levels of SP factor), k = 1, 2, 3, …, r (number of replicates or blocks). Note, the model did not include the three-factor interaction.

Table I: Sketch of the ANOVA Table for Split-Plot Design Model

Source	Df	Sum of Square	Mean Square	F_{cal}
Block	r – 1	SS_{BLOCK}	MS_{BLOCK}	MS_{Block}/MS_{MPE}
A	a – 1	SS_A	MS_A	MS_A / MS_{MPE}
Main plot error	(r – 1)(a – 1)	SS_{MPE}	MS_{MPE}	
B	b – 1	SS_B	MS_B	MS_B / MS_{SPE}
C	c – 1	SS_C	MS_C	MS_C/MS_{SPE}
AB	(a – 1)(b – 1)	SS_{AB}	MS_{AB}	MS_{AB} / MS_{SPE}
AC	(a – 1)(c – 1)	SS_{AC}	MS_{AC}	MS_{AC} / MS_{SPE}
BC	(b – 1)(c – 1)	SS_{BC}	MS_{BC}	MS_{BC} / MS_{SPE}
Split-plot error	a(r-1)(b – 1)(c – 1)	SS_{SPE}	MS_{SPE}	
TOTAL	abcr-1	SS_{TOTAL}		

Source: Jones and Nachtcheim (2009)

where,

$$SS_{TOTAL} = \sum_i^a \sum_j^b \sum_l^c \sum_k^r Y_{ijkl}^2 - \frac{Y_{....}^2}{abcr},\ SS_{BLOCK} = \sum_k^r \frac{Y_{...k}^2}{abc} - \frac{Y_{....}^2}{abcr},\ SS_A = \sum_i^a \frac{Y_{i...}^2}{bcr} - \frac{Y_{....}^2}{abcr},$$

$$SS_{MPE} = \sum_i^a \sum_k^r \frac{Y_{i..k}^2}{bc} - \sum_i^a \frac{Y_{i...}^2}{bcr} - \sum_k^r \frac{Y_{...k}^2}{abc} + \frac{Y_{....}^2}{abcr},\ SS_B = \sum_j^b \frac{Y_{.j..}^2}{acr} - \frac{Y_{....}^2}{abcr},\ SS_C = \sum_l^c \frac{Y_{..l.}^2}{abr} - \frac{Y_{....}^2}{abcr}$$

$$SS_{AB} = \sum_i^a \sum_j^b \frac{Y_{ij..}^2}{cr} - \sum_i^a \frac{Y_{i...}^2}{bcr} - \sum_j^b \frac{Y_{.j..}^2}{acr} + \frac{Y_{....}^2}{abcr},\ SS_{AC} = \sum_i^a \sum_l^c \frac{Y_{i.l.}^2}{br} - \sum_i^a \frac{Y_{i...}^2}{bcr} - \sum_l^c \frac{Y_{..l.}^2}{abr} + \frac{Y_{....}^2}{abcr} \text{ and}$$

$$SS_{BC} = \sum_j^b \sum_l^c \frac{Y_{.jl.}^2}{ar} - \sum_j^b \frac{Y_{.j..}^2}{acr} - \sum_l^c \frac{Y_{..l.}^2}{abr} + \frac{Y_{....}^2}{abcr}$$ hence, the split-plot error will be,

$$SS_{SPE} = SS_{TOTAL} - SS_{BLOCK} - SS_A - SS_{MPE} - SS_B - SS_C - SS_{AB} - SS_{AC} - SS_{BC}$$

2.2 Randomized Complete Block Design Model (RCBD)

Three models can be identified from a randomized complete block design, they are;

1. RCBD model without replication within blocks and one observation per cell.

$$Y_{ij} = \mu + \alpha_i + \beta_j + \ell_{ij} \quad \textbf{(2)}$$

where;
Y_{ij} is the response yield; μ is the overall mean; α_i is the effect of the i^{th} row (treatment); β_i is the effect of the j^{th} column (block) and ℓ_{ij} is the experimental error which is NID ~ $(0, \sigma^2)$; $i = 1, 2, 3,\ldots, p$ $j = 1, 2, 3,\ldots, b$.

2. RCBD model with replication within blocks but no interaction between treatments.

$$Y_{ijkl} = \mu + \alpha_i + \beta_j + \delta_{(i)k} + \ell_{(ijk)l}$$

(3)

where;
Y_{ijkl} is the response from the l^{th} experimental unit in block i, the k^{th} randomization and given the j^{th} treatment; μ is the overall mean; α_i is the i^{th} block effect; β_j is the j^{th} treatment effect; $\delta_{(i)k}$ is the k^{th} restriction error within the i^{th} block (i.e. Df for $\delta_{(i)k}$ is zero) and ℓ_{ijk} is the experimental error, NID~ $(0, \sigma^2)$.

3. RCBD model with replication within blocks and interaction between treatments.

$$Y_{ijkl} = \mu + \alpha_i + \delta_k + \beta_j + \eta_l + (\alpha\beta)_{ij} + (\alpha\eta)_{il} + (\beta\eta)_{jl} + \ell_{ijkl} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(4)}$$

where;
Y_{ijk}, is the k^{th} response from the i^{th} and j^{th} effects; μ, is the overall mean constant; α_i, is the i^{th} effect of treatment A; δ_k, is the block effect; β_j, is the j^{th} effect of treatment B; η_l, is the l^{th} effect of treatment C; $(\alpha\beta)_{ij}$, $(\alpha\eta)_{il}$, $(\beta\eta)_{jl}$ are the interaction of the i^{th}, j^{th} and l^{th} effect of treatment A and B, A and C, B and C;

ℓ_{ijk} , is the random error caused by the k^{th} response from the j^{th} effect of B and l^{th} effect of C in the i^{th} effect of A, NID ~ (0, σ^2); i = 1, …, a, j = 1, …, b, l = 1, …, c, k = 1, …, n.

The third model is the adopted model for this research in comparison with the split-plot design model also; the three-factor interaction was not included in the model just to obtain adequate degree of freedom for error to estimate the interaction effect adequately.

Table II: Sketch of the ANOVA Table for the Third RCBD Model

Source	Df	Sum of Square	Mean Square	F_{cal}
Block	r-1	SS_{BLOCK}	MS_{BLOCK}	MS_{Block}/MSE
A	a-1	SS_A	MS_A	MS_A / MSE
B	b-1	SS_B	MS_B	MS_B / MSE
C	c-1			
AB	(a-1)(b-1)	SS_{AB}	MS_{AB}	MS_{AB} / MSE
AC	(a-1)(c-1)			
BC	(b-1)(c-1)			
Error	(abc-1)(r-1)	SSE	MSE	
TOTAL	abcr-1	SS_{TOTAL}		

Source: Montgomery (2005).

where,

$$SS_{TOTAL} = \sum_i^a \sum_j^b \sum_l^c \sum_k^r Y_{ijkl}^2 - \frac{Y_{....}^2}{abcr},\ SS_{BLOCK} = \sum_k^r \frac{Y_{...k}^2}{abc} - \frac{Y_{....}^2}{abcr},\ SS_A = \sum_i^a \frac{Y_{i...}^2}{bcr} - \frac{Y_{....}^2}{abcr},$$

$$SS_B = \sum_j^b \frac{Y_{.j..}^2}{acr} - \frac{Y_{....}^2}{abcr},\ SS_C = \sum_l^c \frac{Y_{..l.}^2}{abr} - \frac{Y_{....}^2}{abcr},\ SS_{AB} = \sum_i^a \sum_j^b \frac{Y_{ij..}^2}{cr} - \sum_i^a \frac{Y_{i...}^2}{bcr} - \sum_j^b \frac{Y_{.j..}^2}{acr} + \frac{Y_{....}^2}{abcr},$$

$$SS_{AC} = \sum_i^a \sum_l^c \frac{Y_{i.l.}^2}{br} - \sum_i^a \frac{Y_{i...}^2}{bcr} - \sum_l^c \frac{Y_{..l.}^2}{abr} + \frac{Y_{....}^2}{abcr} \text{ and } SS_{BC} = \sum_j^b \sum_l^c \frac{Y_{.jl.}^2}{ar} - \sum_j^b \frac{Y_{.j..}^2}{acr} - \sum_l^c \frac{Y_{..l.}^2}{abr} + \frac{Y_{....}^2}{abcr}$$

hence, the sum of square error will be;

$SS_{Error} = SS_{TOTAL} - SS_{BLOCK} - SS_A - SS_B - SS_C - SS_{AB} - SS_{AC} - SS_{BC}$

2.3 Efficiency of Split-Plot Design Relative to RCBD

According to Hinkelmann and Kempthorne (2008), experimenters utilize the split-plot design in many instances and circumstances for technical reasons. Under most circumstances, the split-plot design is been used for purely technical and practical reasons, as the levels of some factor can be applied only to large experimental units, which can then be "split" into smaller experimental units for application of the levels of the other factor. This includes also the distinction between hard-to-change and easy-to-change factors in industrial experimentation. It is, however, of interest to evaluate the efficiency of the split-plot design relative to the RCBD with r blocks. The question then is given that we have carried out a split-plot experiment, what would have been MSE for the RCBD? This, of course, determines how much information would have been available for all treatment comparisons. Using the pooled treatment sums of squares with appropriate error sum of squares, that

$r(ab-1)\,MSE = r(a-1)\,MS_{WPE} + ra(b-1)MS_{SPE}$

divide through by r we have

$$E' = \frac{(a-1)MS_{WPE} + a(b-1)MS_{SPE}}{ab-1} \quad \text{.......... 5}$$

where $MSE = E'$ = is a weighted average of mean square WP error and mean square SP error; MS_{WPE}, is the mean square WP error; MS_{SPE}, is the mean square split-plot error; a, is the number of levels of WP factor; b, is the number of levels of SP factor.

From equation (1) and equation (4) the information on all treatment comparisons would then have been proportional to 1/ E'. The information on WP treatments from the split-plot experiment relative to randomized complete block design is then E'/MS_{MPE} *that is less than 1*. For SP treatments and interaction effects from the split-plot experiment relative to the randomized complete block, design is E'/MS_{SPE} *that is greater than 1*. These results express the obvious: that the arrangement of split-plot treatments together within a whole plot results in a lower accuracy on whole plot treatment comparisons and an increased accuracy on other treatment comparisons, the formulas enable a quantitative evaluation of these effects. Recourse should be taken to a split-plot design when experimental conditions necessitates the special arrangement, or when the experimenter is more interested in one factor, which he/she arranges within whole plots, than in the other (Hinkelmann and Kempthorne, 2008).

Equation (5) above as presented by Hinkelmann and Kempthorne (2008) is inadequate for our designed models since its applicability is for two factors only. Hence, for a three-factor design the relative efficiency of the split-plot design over RCBD will be obtained from Table I and II, using the pooled treatment sums of squares with appropriate error sums of squares, that

$r(abc - 1)MSE = r(a - 1)MS_{WPE} + ra(b - 1)(c - 1)MS_{SPE}$

divide through by r we have

$$E' = \frac{(a-1)MS_{WPE} + a(b-1)(c-1)MS_{SPE}}{abc-1} \quad \ldots\ldots 6$$

The interpretations for the two factors as given by Hinkelmann and Kempthorne (2008) and their respective conclusions hold for the three factors too.

3. RESULT

Table III: ANOVA Table for the Split-Plot Model

Source	Df	SS	MS	F_{CAL}	P- Values
Blocks	2	8.972	4.486	30.73	<.0001
FR	1	75.69	75.69	22.15	0.0423
Mp error	2	6.834	3.42	23.41	
GM	4	52.68	13.17	90.22	<.0001
BFS	4	6.905	1.726	11.83	<.0001
FR*GM	4	15.12	3.78	25.90	<.0001
FR*BFS	4	1.62	0.40	2.77	0.0305
GM*BFS	16	0.224	0.014	0.10	1.000
SP Error	112	16.35	0.146		
Total	149	184.394			

Source: Author's computation

Table IV: ANOVA Table for the RCBD Model

Source	Df	SS	MS	F_{CAL}	P- Values
Blocks	2	8.97	4.49	22.06	<.0001
FR	1	75.69	75.69	372.16	<.0001
GM	4	52.68	13.17	64.76	<.0001
BFS	4	6.90	1.73	8.49	<.0001
FR*GM	4	15.12	3.78	18.59	<.0001
FR*BFS	4	1.62	0.405	1.99	0.1005
GM*BFS	16	0.224	0.014	0.07	1.0000
Error	114	23.18	0.203		
Total	149	184.39			

Source: Author's computation

4. DISCUSSION

From equation (5) the weighted mean square error, E' is estimated as,

$E' = 0.165142857$.

Hence, the information on WP treatment from the split-plot experiment relative to randomized complete block design is then,

$(E'/MS_{MPE}) = 0.165142857/3.42$

$= 0.0483 < 1$

While the information on SP treatments from the split-plot experiment relative to randomized complete block design is then

$(E'/MS_{SPE}) = 0.165142857/0.146$

$= 1.131 > 1$

Table III and IV above shows the ANOVA result for the split-plot design and the randomized complete block design respectively. From observation on table III, at $\alpha = 5\%$ significance level, all the main effects FR, GM and BFS are significant since, their p-values are less than $\alpha = 5\%$ significance level. While for the interaction effects FR*GM, FR*BFS and GM*BFS it is observed that GM*BFS is not significant since its p-value of 1.000 is greater than $\alpha = 5\%$ significance level. Likewise, from table IV all main effects are significant while for the interaction effects it is observed that FR*BFS and GM*BFS are not significant since their p-values of 0.1005 and 1.000 respectively are greater than $\alpha = 5\%$ significant level. This is an evidence of the split-plot design superiority over the randomized complete block design. Hence, for a complete proof of the ANOVA results the relative efficiency of the split-plot design over the RCBD was been computed. It was clear when the efficiency of the WP treatment relative to the RCBD computed using equation (6) the value (0.0483) obtained is less than one and that of the sub-plot treatments relative to the RCBD show that the value (1.131) obtained is greater than one. Hence, we can agree on the superiority of the SPD over the RCBD. This result obtained is not far from that obtained by Kowalski and Potcner (2003) though they observed the efficiency of SPD relative to complete randomized design (CRD) using ANOVA results only. The difference between the RCBD and CRD is the block factor besides; the issue of blocking is to improve the design and to remove every element of heterogeneity as much as possible. Hence, the SPD is not an exception, its form of design is to develop an adequate and precise design that can reduce cost, remove heterogeneity and study factors of less and important interest together.

5. CONCLUSION

This research is an attempt to compare the effectiveness of SPD over RCBD. The result obtained clearly put the SPD ahead of the RCBD since from the ANOVA table result for the interaction of the feed rate by the machine blowing fan speed (FR*BFS) is significant from the SPD ANOVA model but not significant from the RCBD ANOVA model at 5% significance level. Likewise, the relative efficiency statistic computed was to compare the two designs and the values obtained also reveal that the SPD model is more efficient relative to the RCBD model. Before embarking on the plan and design of experiment, experimenters should adequately study the type of factors for their experiments to know how important they are for achieving their experimental goals. Because the results from this research shows that the SPD will be more efficient than the RCBD especially when one or some of the factors to be studied are of less importance or is hard-to-change as in the industrial experiments. Instead of avoiding the SPD due to computational complexities as viewed by some experimenters and scholars, a professional should be contacted it will go a long way in reducing biased results in estimating factors significant contribution to the experimental response.

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