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Confounding 2^K Factorial Design to Obtain Optimal yield using Different Organic Manure

Akra, Ukeme Paulinus*, Edet, Effiong Bassey

Department of Statistics, University of Calabar, Calabar, Nigeria

Abstract Confounding is the design technique for arranging complete factorial experiment in blocks, where the block size is smaller than the number of treatment combination in one replicate. In this paper, our interest is to confound 2^5 factorial designs without replications in different block size. We also construct 2^5 in 2–blocks, 4 – blocks and 8 – blocks to minimize systematic error. We used higher order interaction method to confound the treatments in different block sizes. Yate's algorithm technique is used to analyze the entire work. From the results obtained, it shows that confounding ABCDE (where A is animal manure, B is green manure, C is mineral manure, D is compost manure and E is ash manure) in 2 – blocks; 3 and 4 – factor interactions were assumed negligible and only four of 2 – factor interactions were significant at $\alpha = 0.05$. In confounding ABCE & ACDE in 4 – block and ABCE, ABDE & ACDE in 8 – blocks; 3, 4 and 5 – factor interactions were assumed negligible. This revealed that only four of 2 – factor interactions were significant at 5% level of significance. This means that different organic manure interactions (BD, CD, CE, & DE) results in different number of fruits produced per stand of *Carica papaya.* We therefore conclude that factor (A), animal manure do not interact with any of the factor to be insignificant; hence factor (A) is considered to be the best manure that yield more fruits than others manure on different blocks.

Keywords Confounding, Factorial experiment, Blocking, Replication, Manure

Introduction

Design of experiments is a discipline that has very broad application across the entire natural and social sciences and even in engineering. The essence of an experiment is to enable the experimenter compare the effects of two or more treatments on some attributes of any experimental material [1]. The goal of an experiment is to determine whether changes in one or more explanatory variables have any effect on some response variable [2]. In its simplest form, an experiment aims at predicting the outcome by introducing a change of the precondition, which is reflected in a variable called the predictor. The change in the predictor is generally hypothesized to result in a change in the outcome variable. An experimental design is the process of planning an experiment, so that appropriate data will be collected which may be analyzed by statistical method resulting in valid and objective conclusions.

Factorial designs are very efficient for studying two or more factors. The effect of a factor can be defined as the change in response produced by a change in the level of the factor. This is referred to as the main effect. In some experiments, it may be found that the difference in the response between levels of one factor is not the same at all levels of the other factors. This is referred to as an interaction effect between factors. Collectively, main effects and interaction effects are called the factorial effects [3]. A full factorial design can estimate all main effects and higher-order interactions. Carrillo *et al.*, [4] applied factorial designs with the aim of studying the factors involved in on-fiber derivatization of Strecker aldehydes, furfural, and (*E*)-2-nonenal with *O*-(2,3,4,5,6-pentafluorobenzyl)hydroxylamine in beer. They compared the relative effectiveness of improving the hand hygiene compliance of nurses and increasing the nurse-to-patient ratio by applying a full 2^kfactorial design to the output of an agent-based simulation. Sean *et al*., [5], applied a full 2^kfactorial design on the output of a stochastic, agent-based simulation to compare the effects of the hand hygiene compliance of healthcare workers and the nurse-to-patient ratio on the transmission of MRSA in a 20-bed intensive care unit (ICU).

Factorial design techniques and normal probability chart representation of the results were first applied to identify potent parental CHO cell growth factors in a lean basal medium [6]. The inhibition of copper corrosion by acid extract of *Gnetum africana* was studied using weight loss method of monitoring corrosion rate. The inhibition of *Gnetum africana* on copper corrosion was optimized by application of 2^3 factorial designs [7].

The production and characterization of bioethanol from maize kernel was carried out through fermentation process using a 2^4 factorial experimental design. The maize kernel was milled, cooked, liquefied, saccharise with malt and fermented with yeast. The optimized operating parameters include reaction temperature, reaction time, quantity of yeast and quantity of maize. This study is focus on the production of bioethanol from maize through fermentation process. It also include investigating the effect of reacting parameters such as quantity of yeast, reaction time, reaction temperature and quantity of maize on bioethanol yield using a 2^4 factorial experimental design [8].

Factorial experimental design involves levels of each factor, we can have 2-levels which are the high and low, 3-levels which is high, intermediate and low and so on, but for the purpose of this research we shall be limited. Each level of a factorial design has several factors for example for 2-levels we have 2, 3…k factors, for 3-levels we can also have 2, 3… k factors. Interest here is basically on 2-levels factorial design with five factors which are A, B, C, D and E. If the factors in a factorial design are too many, for instance say 10 factors and the number of treatment in a full factorial design is too high to be logistically feasible then a fractional factorial design may be done in which some of the possible combinations [usually at least] half are omitted. Urom [9], applied factorial design to studied the mean fruit yield of pawpaw with different fertilizers type (N, P, K). Certain high order interactions are involve, it is sometimes difficult to obtain a complete replicate of a factorial design in one block, therefore the concept of confounding is employed.

Confounding is the design technique for arranging complete factorial experiments in blocks, where the block size is smaller than the number of treatment combination in one replicates [10]. The technique causes information about certain treatment effects usually high order interactions to be confounded with blocks. Blocking and confounding in factorial experiments has a wide application especially in industrial experimentation. Ying [11] also highlighted the advantages and disadvantages of confounding; confounding of contrast in the 2^K series is accomplished by placing these treatment combinations corresponding to the positive coefficients in one block and those corresponding to the negative coefficients in another block. When a main effect of factor B is mixed up or affected with the effect of the blocks, then we can say that effect B is being confounded. The blocks that contains the single experiment (1) where all the factors are at low level is called the principal block. The practical meaning of this is that one can make a start in this block when constructing the design.

In an experiment in which experimental treatment is splitted into blocks and the main effects or interaction effects are affected with the mix-up that occurs, then the block effect is called a block confounded or just confounded. The effect to be confounded is normally given in the experiments. Henrik [12], recommended Yates algorithm as a method of data analysis for all 2^K factorial experiment and that it can be extended to even P^K factorial experiment, where p stands for any level and k for any factor.

Methodology

In this section, we used confounding and blocking to construct 2^5 factorial designs in different blocks of different sizes, Yate's algorithm is employed for this purpose.

Yate's algorithm

The Yate's algorithm provides a convenient method for computing effect estimates and sum of squares without stress. In Yate's algorithm there are several steps or order to follow accordingly in analyzing each data before reaching the sum of squares then proceeding to Analysis of Variance table.

The step is as follows:

1. Set up the treatment column following the standard alphabetical order.
2. Set up the total response column to correspond with treatments in step 1.
3. Set up column 1 as follows;
   i. The first half of column 1 is obtained by adding the responses in adjacent pairs.
   ii. The second half of column 1 is obtained by changing the sign of the first entry in each of the pairs in the response column and adding or by backward subtraction of each pairs.
4. Set up column 2 by operating on the entries of column 1 in the same way we obtained column1 by the total response column.
5. Setup column 3, 4, and 5 in the same way we obtained column 1 and column 2, column 3 will be obtained from column 2, column 4 will be obtained from column 3, and column 5 will be obtained from column 4. The numbers of columns obtained depend on the number of factors present.
6. Set up the column for the average effects of each of the main and interaction effects. The average effects is gotten by dividing the last column(i.e. column 5 for this experiment) by $\mathbf{r2^{k-1}}$**,** where k is the number of factors present and r is the number of replicates.
7. Set up the column for sum of squares. This column is gotten by squaring the last column and dividing each entry by $\mathbf{2^k r}$. [13].

(A) Confounding 2^5 factorial design in 2 - blocks

In an experiment with many factors the number of single experiment quickly becomes very large. For practical experimental work, this means that it can be difficult to ensure homogenous experimental conditions for all the single experiment. A generally occurring problem is that in a series of experimental raw materials used that usually comes in the form of batches. The batches of raw material are what constitute the blocks.

For instance;

$$\begin{pmatrix} (1) \\ a \\ b \\ ab \\ c \\ ac \\ bc \\ abc \\ d \\ ad \\ bd \\ abd \\ cd \\ acd \\ bcd \\ abcd \end{pmatrix} \begin{pmatrix} e \\ ae \\ be \\ abe \\ ce \\ ace \\ bce \\ abce \\ de \\ ade \\ bde \\ abde \\ cde \\ acde \\ bcde \\ abcde \end{pmatrix}$$

This is a 2^5 factorial design in 2- blocks. The first block is called the principal block.

Illustration 1

In a 2^5 factorial design, ABDE and BCDE are confounded with blocks, show the principal block and the block. In this experiment, ABDE is the effect to be confounded; all the effects that are even corresponding to the effect that is to be confounded are added in the principal block, while others that are odd go into the other block.

$$(i)\quad \begin{array}{c} ABDE \\ \begin{pmatrix} (1) \\ ab \\ abc \\ ad \\ bd \\ acd \\ bcd \\ c \\ ae \\ be \\ ace \\ bce \\ de \\ abde \\ cde \\ abcde \end{pmatrix} \begin{pmatrix} a \\ b \\ ac \\ bc \\ d \\ abd \\ cd \\ abcd \\ e \\ abe \\ ce \\ abce \\ bde \\ acde \\ ade \\ bcde \end{pmatrix} \end{array} \qquad (ii)\quad \begin{array}{c} BCDE \\ \begin{pmatrix} (1) \\ a \\ bc \\ abc \\ bd \\ abd \\ cd \\ acd \\ be \\ abe \\ ce \\ ace \\ de \\ ade \\ bcde \\ abcde \end{pmatrix} \begin{pmatrix} b \\ ab \\ c \\ ac \\ d \\ ad \\ bcd \\ abcd \\ e \\ ae \\ bce \\ abce \\ bde \\ abde \\ cde \\ acde \end{pmatrix} \end{array}$$

The block that contains (1) is called the **principal block.**

(B) Construction of 2^5 in 2^1 blocks each of size 2^{5-1}

In constructing a 2^5 factorial design in 2 blocks each of size 16, we do the following,

1. We choose the treatment or effect to be confounded, usually high order interactions are always chosen to be confounded; the main effects are not confounded to prevent loss of information.
2. We assign to the principal block [i.e the block containing (1)] all treatments that have even number of letters in common with the interaction chosen to be confounded, the rest are added to the other block.

Illustration 2

Let ABCE and ABCDE be the interactions chosen to be confounded in a 2^5 factorial design. We construct the factorial design in 2 blocks each of size 16 as follows;

For a 2^5 the main and interaction effects are as follows (1)

a b ab c ac bc abc d ad bd abd cd acd bcd abcd e ae be abe ce ace bce abce de ade bde abde cde acde bcde abcde.

$$(i)\quad \begin{array}{c} ABCE \\ \begin{pmatrix} (1) \\ ab \\ ac \\ bc \\ d \\ abd \\ acd \\ bcd \\ ae \\ be \\ ce \\ abce \\ ade \\ bde \\ cde \\ abcde \end{pmatrix} \begin{pmatrix} a \\ b \\ c \\ abc \\ ad \\ bd \\ cd \\ abcd \\ e \\ abe \\ ace \\ bce \\ de \\ abde \\ acde \\ bcde \end{pmatrix} \end{array} \qquad (ii)\quad \begin{array}{c} ABCDE \\ \begin{pmatrix} (1) \\ ab \\ ac \\ bc \\ ad \\ bd \\ cd \\ abcd \\ ae \\ be \\ ce \\ abce \\ de \\ abde \\ acde \\ bcde \end{pmatrix} \begin{pmatrix} a \\ b \\ c \\ abc \\ abd \\ acd \\ bcd \\ d \\ e \\ abe \\ ace \\ bce \\ ade \\ bde \\ cde \\ abcde \end{pmatrix} \end{array}$$

(C) Construction of 2^5 in 2^2 blocks each of size 2^{5-2}

In constructing a 2^5 factorial in 4 blocks each of size 8, we do the following.

We choose any two interactions to be confounded, and we also confound their product modulo 2, we assign to the principal block all treatments that have even number of letters in common with these interactions that are independently chosen for confounding, not with their generalized interactions. The content of the other blocks are obtained by taking product modulo 2 between entries in the principal block and any other treatment which has not been assigned.

Illustration 3

Construct and confound 2^5 factorial designs in 4 blocks each of size 8 with the following interactions.

(i) ABE & BCD (ii) BDE &CDE (iii) ABCE & ACDE (iv) ADE & ABC

$$\text{(i)}\quad \overset{ABE}{\begin{pmatrix} (1) \\ abc \\ abd \\ cd \\ bce \\ bde \\ ae \\ acde \end{pmatrix}} \quad \overset{BCD}{\begin{pmatrix} a \\ bc \\ bd \\ acd \\ abce \\ abde \\ e \\ cde \end{pmatrix}} \quad \overset{ACDE}{\begin{pmatrix} b \\ ac \\ ad \\ bcd \\ ce \\ de \\ abe \\ abcde \end{pmatrix} \begin{pmatrix} c \\ ab \\ abcd \\ d \\ be \\ bcde \\ ace \\ ade \end{pmatrix}}$$

$$\text{(ii)}\quad \overset{BDE}{\begin{pmatrix} (1) \\ a \\ bcd \\ abcd \\ bce \\ abce \\ de \\ ade \end{pmatrix}} \quad \overset{CDE}{\begin{pmatrix} b \\ ab \\ cd \\ acd \\ ce \\ ace \\ bde \\ abde \end{pmatrix}} \quad \overset{BC}{\begin{pmatrix} c \\ ac \\ bd \\ abd \\ be \\ abe \\ cde \\ acde \end{pmatrix} \begin{pmatrix} d \\ ad \\ bc \\ abc \\ bcde \\ abcde \\ e \\ ae \end{pmatrix}}$$

$$\text{(iii)}\quad \overset{ABCD}{\begin{pmatrix} (1) \\ ac \\ abd \\ bcd \\ ae \\ ce \\ bde \\ abcde \end{pmatrix}} \quad \overset{ACDE}{\begin{pmatrix} a \\ c \\ bd \\ abcd \\ e \\ ace \\ abde \\ bcde \end{pmatrix}} \quad \overset{BD}{\begin{pmatrix} b \\ abc \\ ad \\ cd \\ abe \\ bce \\ de \\ acde \end{pmatrix} \begin{pmatrix} d \\ acd \\ ab \\ bc \\ ade \\ cde \\ be \\ abce \end{pmatrix}} \quad (iv) \quad \overset{ADE}{\begin{pmatrix} (1) \\ bc \\ abd \\ acd \\ abe \\ ace \\ de \\ bcde \end{pmatrix}} \quad \overset{ABC}{\begin{pmatrix} a \\ abc \\ bd \\ cd \\ be \\ ce \\ ade \\ abcde \end{pmatrix}} \overset{BCDE}{\begin{pmatrix} b \\ c \\ ad \\ abcd \\ ae \\ abce \\ ade \\ cde \end{pmatrix} \begin{pmatrix} d \\ bcd \\ ab \\ ac \\ abde \\ acde \\ e \\ bce \end{pmatrix}}$$

(D) Construction of 2^5 In 2^3 blocks each of size 2^{5-3}

In constructing a 2^5 factorial design in 8 blocks each of size 4; we do the following:

1. We chose any three interactions to be confounded and note that their product modulo 2 is also confounded, i.e. their generalized interactions.
2. We assign to the principal block all treatment that are have even number of letters in common with the interactions that were independently chosen for confounding, not with their generalized interactions. The content of the other blocks are obtained by taking product modulo 2 between entries in the principal block and any other treatment which has not been assigned.

Illustration 4

Construct a 2^5 factorial design in 8 blocks each of size 4 with the following interactions to be confounded with blocks.

(i) ABC,ABD & CDE

(ii) ABCE, ABDE & ACDE

$$
\text{(i)}\quad \begin{array}{cccccccc} ABC & ABD & CDE & CD & BDE & ABCD & ABDE & ACD \\ \begin{pmatrix}(1)\\ ab\\ acd\\ bcd\end{pmatrix} & \begin{pmatrix}a\\ b\\ cd\\ abcd\end{pmatrix} & \begin{pmatrix}c\\ abc\\ ad\\ bd\end{pmatrix} & \begin{pmatrix}d\\ abd\\ ac\\ bc\end{pmatrix} & \begin{pmatrix}e\\ abe\\ acde\\ bcde\end{pmatrix} & \begin{pmatrix}ae\\ be\\ cde\\ abcde\end{pmatrix} & \begin{pmatrix}ce\\ abce\\ ade\\ bde\end{pmatrix} & \begin{pmatrix}de\\ abde\\ ace\\ bce\end{pmatrix} \end{array}
$$

The first three are the effects chosen to be confounded, we check those interactions which are even corresponding to these three interactions chosen and place them in the principal block, then the other blocks are obtain by multiplying effects which has not been assigned with the principal blocks.

$$
\text{(ii)}\quad \begin{array}{cccccccc} ABCE & ABDE & ACDE & CE & BD & BC & BE & DC \\ \begin{pmatrix}(1)\\ bcd\\ ae\\ abcde\end{pmatrix} & \begin{pmatrix}a\\ abcd\\ e\\ bcde\end{pmatrix} & \begin{pmatrix}b\\ cd\\ abe\\ acde\end{pmatrix} & \begin{pmatrix}c\\ bd\\ ace\\ abde\end{pmatrix} & \begin{pmatrix}d\\ bc\\ ade\\ abce\end{pmatrix} & \begin{pmatrix}be\\ cde\\ ab\\ acd\end{pmatrix} & \begin{pmatrix}ac\\ abd\\ ce\\ bde\end{pmatrix} & \begin{pmatrix}ad\\ abc\\ de\\ bce\end{pmatrix} \end{array}
$$

The same way too, the first three interactions were chosen independently for confounding and were obtained the same way as in the first example, then the contents of the other blocks were obtained by randomly choosing any effect which has not been assigned and multiply it with the principal block.

An experimental design approach

An agriculturist examine five factor of organic manure; animal manure (A), green manure (B), mineral manure (C), compost manure (D) and ash (E) to improve soil at two levels (plots) to obtain the numbers of fruit per stand of *carica papaya*. This is a possibility that different factor combinations may result in different number of fruits (interaction effect present) produced by carica papaya. The mean yield of the crop tested with five factors each at two levels without replication is shown below:

Table 1: 2^5 factorial design of *carica papaya*

Treatment combinations	**Numbers of fruit per stand**
(1)	10
a	5
b	15
ab	13
c	6
ac	9
bc	3
abc	14
d	20
ad	19
bd	17
abd	4
cd	9
acd	6
bcd	7
abcd	8
e	2
ae	10
be	15
abe	8
ce	11
ace	18

bce	15
abce	20
de	11
ade	5
bde	9
abde	6
cde	4
acde	10
bcde	3
abcde	7

Below is the data analysis for 2^5 factorial design without replication using Yate's algorithm.

Table 2

Treatment combination	Total response	1	2	3	4	5	Average effects	Sum of Square
(1)	10	15	43	75	165	328	20.50	3362.00
a	5	28	32	90	163	5	0.31	0.78
b	15	15	60	99	-9	8	0.50	2.00
ab	13	17	30	64	14	-15	-0.94	7.03
c	6	39	35	7	-3	-15	-0.94	7.03
ac	9	21	64	-16	11	31	1.94	30.03
bc	3	15	30	13	3	0	0.00	0.00
abc	14	15	24	1	-18	29	1.81	26.28
d	20	12	-7	15	-38	-20	-1.25	12.50
ad	19	23	14	-18	23	-35	-2.19	38.28
bd	17	29	-14	17	19	-56	-3.50	98.00
abd	4	35	-2	-6	12	-1	-0.06	0.031
cd	9	16	1	11	7	-57	-3.56	101.53
acd	6	14	12	-8	-7	-5	-0.31	0.78
bcd	7	14	-9	-17	21	26	1.63	21.13
abcd	8	10	10	1	8	-7	-0.44	1.53
e	2	-5	13	-8	15	-2	-0.13	0.13
ae	10	-2	2	-30	-35	23	1.44	16.53
be	15	3	-18	29	-23	14	0.88	6.13
abe	8	11	0	-6	-12	-21	-1.31	13.78
ce	11	-1	11	7	-33	61	3.81	116.28
ace	18	-13	6	12	-23	31	1.94	30.03
bce	15	-3	-2	11	-19	-14	-0.88	6.13
abce	20	1	-4	1	18	-13	-0.81	5.28
de	11	8	3	-11	-22	-50	-3.13	78.13
ade	5	-7	8	18	-35	11	0.69	3.78
bde	9	7	-12	-5	5	10	0.63	3.13
abde	6	5	4	-2	-10	37	2.31	42.78
cde	4	-6	-15	5	29	-13	-0.81	5.28
acde	10	-3	-2	16	3	-15	-0.94	7.03
bcde	3	6	3	13	11	-26	-1.63	21.13
abcde	7	4	-2	-5	-18	-29	-1.81	26.28

(E) Analysis of 2^5 factorial design with confounding

(i) In constructing 2^5 in 2 blocks each of 16 sizes, below is the Analysis of Variance for this confounding with ABCDE confounded with blocks and without replication.

$$\overset{ABCDE}{\begin{pmatrix} (1)=10 \\ ab=13 \\ ac=9 \\ bc=3 \\ ad=19 \\ bd=17 \\ cd=9 \\ abcd=8 \\ ae=10 \\ be=15 \\ ce=11 \\ abce=20 \\ de=11 \\ abde=6 \\ acde=10 \\ bcde=3 \end{pmatrix} \begin{pmatrix} a=5 \\ b=15 \\ c=6 \\ abc=14 \\ abd=4 \\ acd=6 \\ bcd=7 \\ d=20 \\ e=2 \\ abe=8 \\ ace=18 \\ bce=15 \\ ade=5 \\ bde=9 \\ cde=4 \\ abcde=7 \end{pmatrix}}$$

Assuming all 3 & 4 factor interactions is negligible.

Table 3: ANOVA table for confounding 2^5 In 2- blocks

S/V	DF	SS	MS	F-ratio
Block(ABCDE)	1	26.18	26.18	2.08
A	1	0.78	0.78	0.06
B	1	2.00	2.00	0.16
C	1	7.03	7.03	0.56
D	1	12.50	12.50	0.99
E	1	0.13	0.13	0.01
AB	1	7.03	7.03	0.56
AC	1	30.03	30.03	2.39
AD	1	38.28	38.28	3.05
AE	1	16.53	16.53	1.32
BC	1	0.00	0.00	0.00
BD*	1	98.00	98.00	7.81
BE	1	6.13	6.13	0.49
CD*	1	101.53	101.53	8.10
CE*	1	78.13	78.13	9.27
DE*	1	188.04	12.54	6.23
Error(4&5)	15	540.56		
Total	31			

Critical region: $F_{cal} > F_{tab,0.05(1,15)} = 6.20$ in all case

From the ANOVA table above, it can be seen that only BD, CD, CE and DE are significant at $\alpha = 0.05$.

(ii) In constructing 2^5 factorial design in 4 blocks each of 8 sizes, ABCE and ACDE were confounded with blocks and without replication.

$$\overset{ABCE}{\begin{pmatrix} (1)=10 \\ ac=9 \\ abd=4 \\ bcd=7 \\ ae=10 \\ ce=11 \\ bde=9 \\ abcde=7 \end{pmatrix}} \quad \overset{ACDE}{\begin{pmatrix} a=5 \\ c=6 \\ bd=17 \\ abcd=8 \\ e=2 \\ ace=18 \\ abde=6 \\ bcde=3 \end{pmatrix}} \quad \overset{BD}{\begin{pmatrix} b=15 \\ abc=14 \\ ad=19 \\ cd=9 \\ abe=8 \\ bce=15 \\ de=11 \\ acde=10 \end{pmatrix} \begin{pmatrix} d=20 \\ acd=6 \\ ab=13 \\ bc=3 \\ ade=5 \\ cde=4 \\ be=15 \\ abce=20 \end{pmatrix}}$$

Assuming all 3, 4 & 5-factor interaction is negligible.

Table 4: ANOVA table for confounding 2^5 in 4 blocks

S/V	df	SS	MS	F-ratio
Blocks (ABCE & ACDE)	2	12.31	6.16	0.43
A	1	0.78	0.78	0.05
B	1	2.00	2.00	0.14
C	1	7.03	7.03	0.49
D	1	12.50	12.50	0.87
E	1	0.13	0.13	0.01
AB	1	7.03	7.03	0.49
AC	1	30.03	30.03	2.08
AD	1	38.28	38.28	2.65
AE	1	16.53	16.53	1.15
BC	1	0.00	0.00	0.00
BD*	1	98.00	98.00	6.80
BE	1	6.13	6.13	0.42
CD*	1	101.53	101.53	7.04
CE*	1	116.28	116.28	8.06
DE*	1	78.13	78.13	5.41
Error	14	202.06	14.43	
Total	31	728.75		

Critical region: $F_{cal} > F_{o.o5(1,14)} = 4.60$

From the ANOVA above, only interaction BD, CD, CE & DE are significant.

(iii) In constructing 2^5 factorial design in 8 blocks each of 4 sizes, ABCE,ABDE and ACDE were confounded with blocks and without replication.

$$\begin{array}{ccccccc} ABCE & ABDE & ACDE & CE & BD & BC & BE \\ \begin{pmatrix} (1)=10 \\ bcd=7 \\ ae=10 \\ abcde=7 \end{pmatrix} & \begin{pmatrix} a=5 \\ abcd=8 \\ e=2 \\ bcde=3 \end{pmatrix} & \begin{pmatrix} b=15 \\ cd=9 \\ abe=8 \\ acde=10 \end{pmatrix} & \begin{pmatrix} c=6 \\ bd=17 \\ ace=18 \\ abde=6 \end{pmatrix} & \begin{pmatrix} d=20 \\ bc=3 \\ ade=5 \\ abce=20 \end{pmatrix} & \begin{pmatrix} be=3 \\ cde=4 \\ ab=13 \\ acd=6 \end{pmatrix} & \begin{pmatrix} ac=9 \\ abd=4 \\ ce=11 \\ bde=9 \end{pmatrix} \end{array}$$

$$\begin{array}{c} DC \\ \begin{pmatrix} ad=19 \\ abc=14 \\ de=11 \\ bce=15 \end{pmatrix} \end{array}$$

Assuming all 3, 4 & 5-factor interactions is negligible.

Table 5: ANOVA table for confounding 2^5 in 8 blocks

S/V	df	SS	MS	F-ratio
Blocks (ABCE, ABDE & ACDE)		55.09	18.36	1.50
A	3	0.78	0.78	0.06
B	1	2.00	2.00	0.16
C	1	7.03	7.03	0.57
D	1	12.50	12.50	1.02
E	1	0.13	0.13	0.01
AB	1	7.03	7.03	0.57
AC	1	30.03	30.03	2.45
AD	1	38.28	38.28	3.12

AE	1	16.53	16.53	1.35
BC	1	0.00	0.00	0.00
BD*	1	98.00	98.00	8.00
BE	1	6.13	6.13	0.50
CD*	1	101.53	101.53	8.29
CE*	1	116.28	116.28	9.50
DE*	1	78.13	78.13	6.38
Error	13	159.28	12.25	
Total	31	673.66		

Critical region: $F_{cal} > F_{0.05,(1,13)} = 4.67$

From the ANOVA above, only BD, CD, CE & DE are significant at 5%.

Result and Discussion

Based on the results obtained from constructing 2^5 design in two (2) blocks of 16 sizes, three (3) and four (4) factors interaction were negligible. In constructing 2^5 factorial design in four (4) blocks each of eight (8) size and ABCE and ACDE were confounded without replication neglecting three (3), four (4) and five (5) factors interactions. Also in constructing 2^5 in eight (8) blocks each of four (4) sizes, ABCE, ABDE and ACDE were confounded without replication. Hence all the designs constructed and confounded with different blocks sizes neglecting three (3), four (4) and five (5) factors interactions in all cases, only BD, CE, CD and DE factor interactions are significant at 5% level of significance.

Montgomery, D. (2013). Design and analysis of experiments (8th ed.). Hoboken, NJ: John Wiley & Sons, Inc.From the results obtain, it shows that all the block sizes were reduced. And only interaction BD, CD, CE & DE were significant in the confounding of ABCDE in 2 blocks, ABCE & ACDE in 4 blocks and ABCE, ABDE & ACDE in 8 blocks at 5% level of significance. This means that different factor (i.e. organic manure) interactions results in different number of fruits produced per stand of carica papaya. It also shows that factor (A) animal manure do not interact with another factor to be insignificant; therefore factor (A) is considered to be the best manure among others. The result in confounding 25 in 8 – blocks minimizes systematic error in different manure type which makes the plots (blocks) more fertile to produce more fruits. Therefore, the optimal fruit yield is obtained in these blocks.

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