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EFFECT OF POULTRY DUNG AND ORGANOMINERAL FERTILIZER ON THE GROWTH OF MAIZE

Olayinka Olusegun Oladipupo

The Bible Society of Nigeria, Osun Area,
3, Ayedun Street, Opposite Seventh Day Adventist Church,
Ayetoro, Osogbo, Osun State, Nigeria

ABSTRACT: This project is aimed at determining the effect of poultry dung and organomineral fertilizer on the growth of maize (plant height) at different stations (Apomu, Iwo and Jago).
Response Surface Methodology, the first- order and the second- order models are used to determine the optimal plant height for given level of each of the variables or factors considered. Each location needs different requirement of fertilizer application, Apomu and Jago locations need the average of 83kg/ha of poultry-dung while Iwo location needs as much as 100kg/ha of organomineral to produce the optimum plant height.

KEYWORDS: POULTRY DUNG, ORGANOMINERAL FERTILIZER, MAIZE.

1 INTRODUCTION

We consider here the Response Surface Methodology (RSM) as a tool to determine the region where the optimal response occur and the effect of poultry dung and organomineral fertilizer on the growth of maize. For this project work, the plant growth y is the response variable and it is a function of poultry-dung and organomineral. It can be expressed as: $y= f(x_1, x_2) +e$. In most (RSM) problems; the true response function f is unknown. In order to develop a proper approximation for f, the experimenter usually starts with a low- order polynomial in some small region. If the response can be defined by a linear function of independent variables, then the approximating function is a first-order model. A first-order model with 2 independent variables can be expressed as

$$y= \beta o +\beta_1X_1+ \beta_2X_2 + \varepsilon$$

If there is a curvature in the response surface, then a higher degree polynomial should be used. The approximating function with 2 variables of a second- order model is given as

$$y= \beta o+\beta_1X_1+\beta_2X_2+ \beta_{11}X^2{}_{11} + \beta_{22}X^2{}_{22} + \beta_{12}X_1X_{2\,+}\,\varepsilon$$

According to Hill and Hunter, Response Surface Methodology method was introduced by G.E.P. Box and K. B. Wilson in 1951 (Wikipedia 2006). Box and Wilson suggested using a first degree polynomial method to approximate the Response variable. They acknowledge that this model is only an approximation, not accurate, but such a model is easy to estimate and apply, even when little is known about the process (Wikipedia 2006). For the second-order model, many subject-matter Scientists and Engineers have a working knowledge of the Central Composite Design (CCDs). According to (Myers, Khur, and Carter 1989), the important development of optimal design theory in the field experimental design emerged following Word World II. Elfving (1959), Chernoff (1953), Kiefer (1962) and Keifer and Wolfforwitz were some of the various authors who published their work on optimality. Edwards (1991; 1994), Edwards and Harrison (1993) and Edwards and Parry (1993) has revealed that polynomial regression analysis is a procedure capable to overcome these methodological problems. The objective of studying RSM and based on this project can be accomplished by: understanding the topography of the response surface (Local maximum, local minimum, ridge lines) and finding the region where the optimal response occurs. The goal is to move rapidly and efficiently along a path to get a maximum or a minimum response so that the response is optimized. The data used in this research work is a secondary data from the Institute of Agricultural Research and Training. Obafemi Awolowo University, Moor Plantation, Ibadan, Nigeria. The data was collected from different locations of experiment i.e Apomu, Iwo and Jago based on Week After Planting (WAP i.e. 2 WAP, 4 WAP and 6 WAP). The treatments used are control, poultry dung at 50kg/ha (P/D_5); Poultry dung at 100kg/ha (P/D_{10}); Organomineral at 50kg/ha (OM_5); Organomineral at 100kg/ha (OM_{10}); Combination of P/D_5 and $OM_{10;}$ combination of P/D_{10} and OM_5; combination of P/D5 and OM_5; and combination of P/D_{10} and OM_{10}

2 METHODOLOGY

RESPONSE SURFACE METHODS AND DESIGN

RSM are designs and models for working with continuous treatments when finding the optima or describing the response is the goal. The first goal for Response Surface Method is to find the optimum response. When there is more than one response then it is important to find the compromise optimum that does not optimized only one response. When these are constraints on the design data, then the experimental design has to meet requirements of the constraints.

The second goal is to understand how the response changes in a given direction by adjusting the design variables. In general, the response surface can be visualized graphically. The graph is helpful to see the shape of a response surface: hills, valleys, and ridge lines.

Hence, the function f (x_1, x_2) can be plotted versus the factors of x_1 and x_2 as shown as Figure A

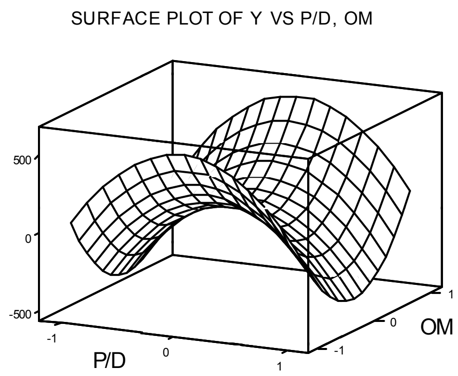

Figure A

In this graph, each value of P/D and OM generates a y-value. This three-dimensional graph shows the response from the side and it is called a response surface plot.

Sometimes, it is less complicated to view the response surface in two-dimensional graphs. The contour plots can show contour lines of P/D and OM pairs that have the same response value y. An example of contour plots is as shown in Figure B

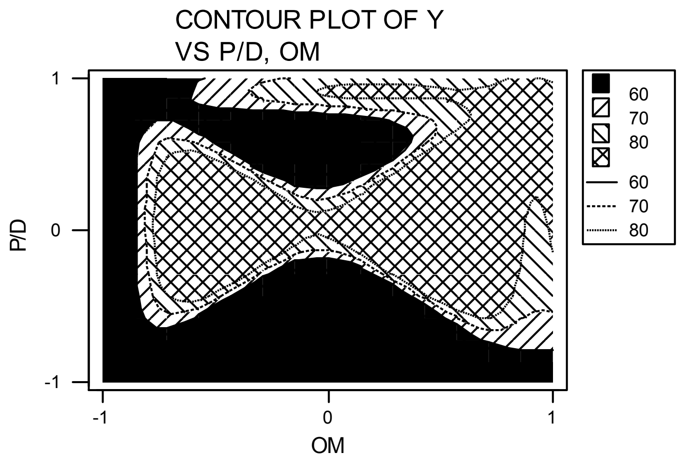

Figure B - Contour plot

In order to understand the surface of a response, graphs are helpful tools. But, when there are more than two independent variables, graphs are difficult or almost impossible to use to illustrate the response surface, since it is beyond 3-dimention. For this reason, response surface models are essential for analyzing the unknown function f.

The relationship between the response variable y and independent variables is usually unknown. In general, the low-order polynomial model is used to describe the response surface f. A polynomial model is usually a sufficient approximation in a small region of the response surface. Therefore, depending on the approximation of unknown function f, either first-order or second-order model are employed. A first-order model is a multiple-regression model and the β_j's are regression coefficients.

When there is a curvature in the response surface the first-order model is insufficient. A second-order model is useful in approximating a portion of the true response surface with parabolic curvature. The second-order model includes all the terms in the first-order model, plus all quadratic terms like $\beta_{11}x^2_{1i}$ **.**

There are many designs available for fitting a second-order model. The most popular one is the central composite design (CCD). This is a very useful tool to determine the optimal level of a response variable; a CCD was used for response optimization. This design was introduced by Box and Wilson. It consists of factorial points, central points and axial points.

The analysis of a second-order model is usually done by computer software. The analysis of variance for fitting the data to the second-order and surface plots will help characterize the response surface. In this project, my goal is to fit the second-order model using central composite design. I will investigate the adequacy of the second-order model for plant height of poultry dung and organomineral.

RESPONSE SURFACE STATISTICAL MODEL

In general, the response surface can be visualized graphically. The graph is helpful to see the shape of a response surface; hills, valleys and ridge lines.

In order to develop a proper approximation for f, the experimenter usually starts with a low-order polynomial. If the response can be defined by a linear function of independent variables, then the approximating function is a **first-order model.**

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + e$$

If there is a curvature in the response surface, then a higher degree polynomial should be used. The approximating function with 2 variables is called a **second-order model:**

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x^2_{11} + \beta_{22} x^2_{22} + \beta_{12} x_1 x_2 + e$$

To test for the significance of the regression i.e. independent variables poultry dung and organomineral contribute significantly to the response variable plant height of 6 weeks after planting. Analysis of variance, regression analysis and lack of fit test were used to examine the model. Furthermore, Minitab was used to conduct the regression analysis and the variance of analysis of Plant height for three locations (Apomu, Iwo & Jago) 6 WAP.

LACK OF FIT TEST

Regression models are often fitted to data when the true functional relationship is unknown. Naturally, we would like to know whether the order of the model tentatively assumed is correct. Once the estimated equation is obtained, an experimenter can obtain the ANOVA statistics (F-test, R^2, the adjusted R^2 and lack of fit), to determine adequacy of the fitted model. If there is a significant lack of fit of the first-order model, then a more highly structured model, such as second-order model may be studied in order to locate the optimum. When the first-order model shows a significant lack of fit, then an experimenter can use a second-order model to describe the response surface. The lack of fit of the first order model occurs when the model does not adequately represent the mean response as a function of the factor level. The hypotheses we wish to test are

H_o: The model adequately fits the data

H_1: The model does not fit the data

H_o is rejected when p-value for the statistic F is less than the significant level α (0.05).

How well the estimate model fits the data can be measured by the value of R^2. The R^2 lies in the interval [0, 1]. When R^2 is closer to the 1, the better the estimation of regression equation fits the sample data. In general, the R^2 measures percentage of the variation of y around y that is explained by the regression equation. Thus, some experimenter rather uses adjusted-R^2.

3 RESULTS AND DISCUSSION

The central core of the analysis of an experimental design, irrespective of the model lies in the partitioning of the total sum of squares (for the responses) into meaningful and distinct portions. To see how this is done for our present model, let us start the analysis for each location based on period of weeks after planting. For this project, factors P/D, OM and P/D*OM is replaced by poultry dung, Organomineral and combination of poultry dung and Organomineral.

Finding the region where the optimal response occurs**.** In this case, the plant height y is the response variable, and it is a function of poultry dung and organomineral. It can be expressed as $y = f(x_1, x_2) + e$

REGRESSION ANALYSIS OF LACK OF FIT: PLANT HEIGHT FOR APOMU VERSUS P/D, OM

The regression equation is

```
PLANT HEIGHT = 72.1 + 8.71 P/D + 7.57 OM

Predictor        Coef     SE Coef        T        P
Constant       72.051       4.515    15.96    0.000
P/D             8.713       2.765     3.15    0.004
OM              7.574       2.765     2.74    0.011

S = 11.73            R-Sq = 42.1%         R-Sq(adj) = 37.2%
PRESS = 4294.80      R-Sq(pred) = 24.68%
```

Analysis of Variance

```
Source            DF        SS        MS       F       P
Regression         2    2399.3    1199.6    8.72   0.001
Residual Error    24    3303.0     137.6
  Lack of Fit      6    2798.8     466.5   16.65   0.000
  Pure Error      18     504.2      28.0
Total             26    5702.3
```

The p-value for lack of fit is p= 0.000. Hence, we shall reject the null hypothesis; there is significant evidence of lack of fit. Therefore, there is curvature in the response surface which will lead to the Second-Order Model

The contour plot in Figure C shows how the response variable relates to the two factors, each at three levels. The levels of factor refer to as low, intermediate and high, represented by the digit 0 (low), 1 (intermediate) and 2 (high). The response surface changes when the holding levels are changed.

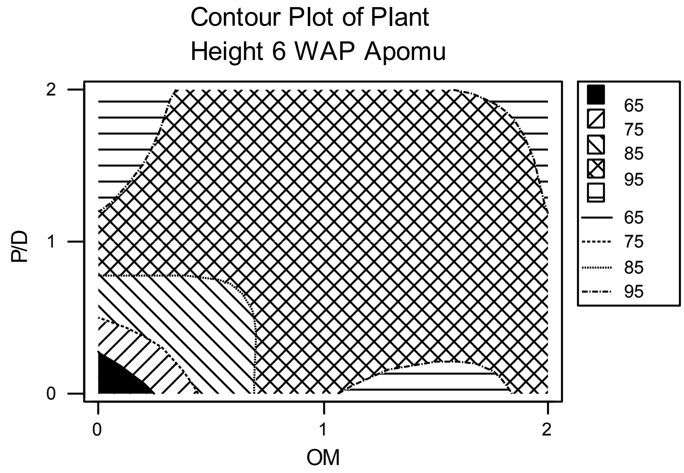

Figure C

When there is a curvature in the response surface the first-order model is insufficient. A second-order model is useful in approximating a portion of the true response surface with parabolic curvature. The second-order model includes all the terms in the first order model, plus all quadratic terms like $\beta_{11} x^2_{1i}$

It is usually expressed as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x^2_{11} + \beta_{22} x^2_{22} + \beta_{12} x_1 x_2 + e$$

The analysis of a second-order model was done by computer software. The analysis of variance for fitting the data to the second-order and contour plots will help characterized the response surface. In this section, the goal is to fit the second-order model using central composite design.

RESPONSE SURFACE REGRESSION: PLANT HEIGHT FOR APOMU VERSUS P/D, OM

The analysis was done using uncoded units.

Estimated Regression Coefficients for P H APOM

Term	Coef	SE Coef	T	P
Constant	93.6	1.12	83.349	0.000
P/D	7.8	2.69	2.907	0.008
OM	8.3	2.69	3.075	0.006
P/D*P/D	132.2	1077.08	0.123	0.903
OM*OM	-167.8	1077.08	-0.156	0.878
P/D*OM	8.1	2.69	3.012	0.007

S = 5.385   R-Sq = 89.3%   R-Sq(adj) = 86.8%

Analysis of Variance for P H APOMU

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	5093.2	5093.2	1018.64	35.12	0.000
Linear	2	519.4	519.4	259.69	8.95	0.002
Square	2	4310.7	4310.7	2155.37	74.32	0.000
Interaction	1	263.1	263.1	263.09	9.07	0.007
Residual Error	21	609.1	609.1	29.00		
Lack-of-Fit	3	115.4	115.4	38.46	1.40	0.275
Pure Error	18	493.7	493.7	27.43		
Total	26	5702.3				

The comparison shows that p=0.275 is greater than the significant level α (0.05). There is no significant evidence of lack of fit. Both the R^2 = 89.3% and R^2 (adj) = 86.8% are statistically significant for the response variable. The analysis of variance indicates that there are significant interactions between the factors. The small p-value for linear (main effect) and squared term also point out that their contribution is significant to the model.

The fitted response for the above regression model was plotted in Figure below; graphs were generated for the pair-wise combination of the two factors while the other one is the optimum levels for plant height. Graphs are given here to highlight the roles played by factors.

Surface Plot of poultry dung (*P/D*) and organomineral (*OM*) on the plant height for Apomu station

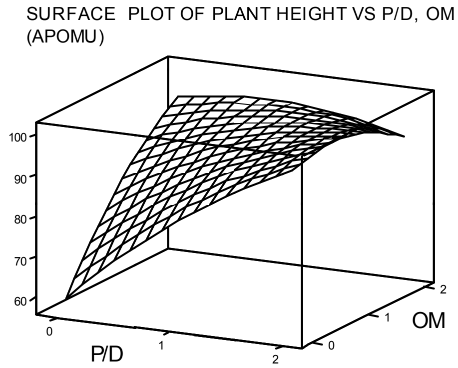

Figure D

RESPONSE OPTIMIZATION

Parameters

```
                  Goal      Lower    Target     Upper    Weight    Import
P H APOMU       Maximum        50       150       150         1         1
Starting Point
P/D          =        0
OM           =        0

Local Solution
P/D          =  1.70292    (85kg/ha)
OM           =  0.68549    (34kg/ha)

Predicted Responses
P H APOMU    =  97.4591, desirability =  0.47459

Composite Desirability =  0.47459
```

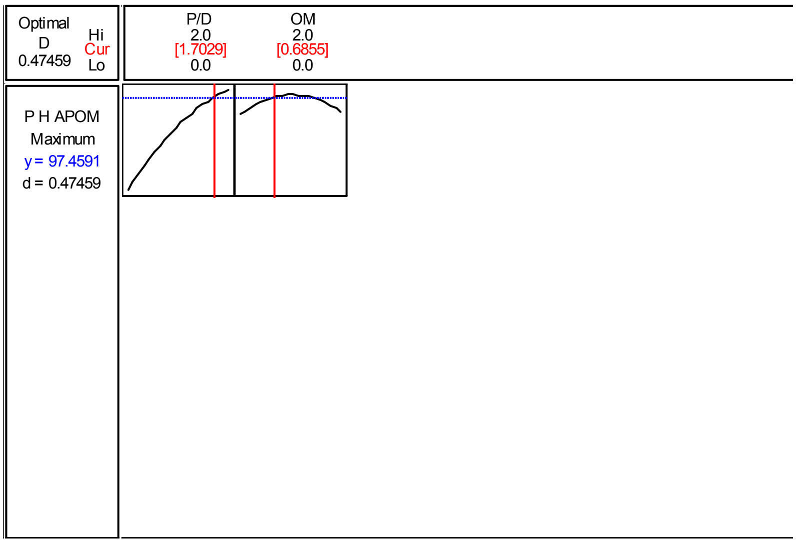

Figure E

Response Surface Regression: Plant Height for Apomu versus P/D, OM Estimated Regression Coefficients for P H APOMU

Term	Coef	SE Coef	T	P
Constant	88.34	1.810	48.797	0.000
P/D	8.71	2.217	3.930	0.001
OM	7.57	2.217	3.416	0.002
P/D*OM	-10.28	2.716	-3.785	0.001

S = 9.407 R-Sq = 64.3% R-Sq(adj) = 59.7%

The predicted optimum levels of the tested variables, poultry-dung and organomineral were obtained by applying response optimization on figure E using Minitab package software. The optimal levels for Apomu station were as follows: P/D = 1.70292 (85kg/ha); OM = 0.68549 (34kg/ha) with corresponding predicted response plant height 97.5cm. Verification of the predicted values was conducted by using response surface regression analysis on figure 4.8F; the predicted response plant height is 96.4cm. This result shows the effectiveness of this model.

The First-order model for Iwo station

Regression Analysis of Lack of Fit: Plant Height for Iwo versus P/D, OM

The regression equation is

PLANT HEIGHT = 55.6 + 10.0 P/D + 7.82 OM

Predictor	Coef	SE Coef	T	P
Constant	55.609	3.080	18.05	0.000
P/D	10.011	1.886	5.31	0.000
OM	7.817	1.886	4.14	0.000

S = 8.003 R-Sq = 65.4% R-Sq(adj) = 62.5%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	2903.8	1451.9	22.67	0.000
Residual Error	24	1537.3	64.1		
Lack of Fit	6	600.0	100.0	1.92	0.132
Pure Error	18	937.3	52.1		
Total	26	4441.1			

The comparison shows that p=0.132 is greater than the significant level α (0.05). There is no significant evidence of lack of fit. Therefore, I can conclude that the true response surface is explained by the model and we stop at First-order model. Both the R^2 = 65.4% and R^2(adj)= 62.5% are statistically significant for the response variable

The figure below shows the contour plots of plant height for Iwo to visualize the response surface. Since the response surface is a plane, there is no evidence of lack of fit of the first-order model.

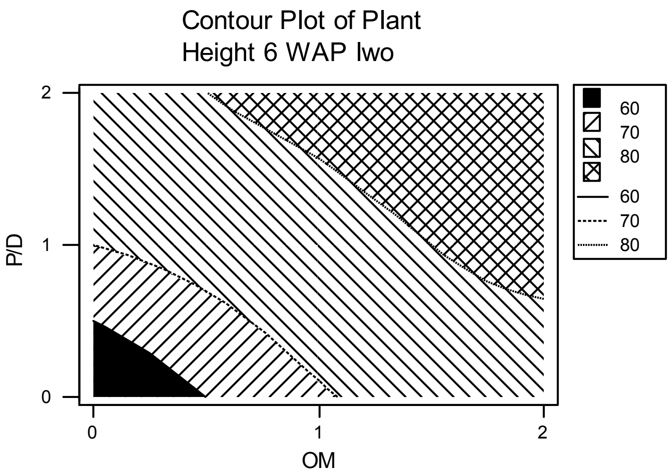

Figure F

The fitted response for the above regression model was plotted in Figure G below.

Surface plot of poultry dung (*P/D*) and organomineral (*OM*) on the plant height for Iwo station

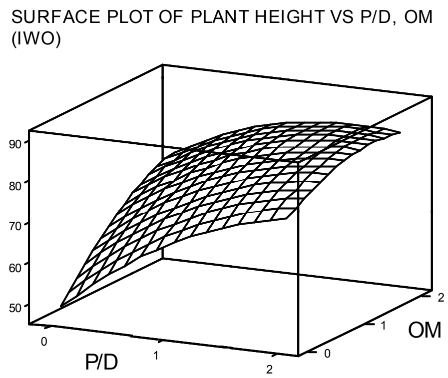

Figure G

Response Optimization

Parameters

```
                    Goal      Lower     Target      Upper     Weight     Import
P H IWO          Maximum         50        150        150          1          1
Starting Point
P/D           =        0
OM            =        0
Local Solution
P/D           =  1.59630    (80kg/ha)
OM            =  2.00000    (100kg/ha)
```

Predicted Responses

```
P H IWO       =  84.9573, desirability =  0.34957
Composite Desirability =  0.34957
```

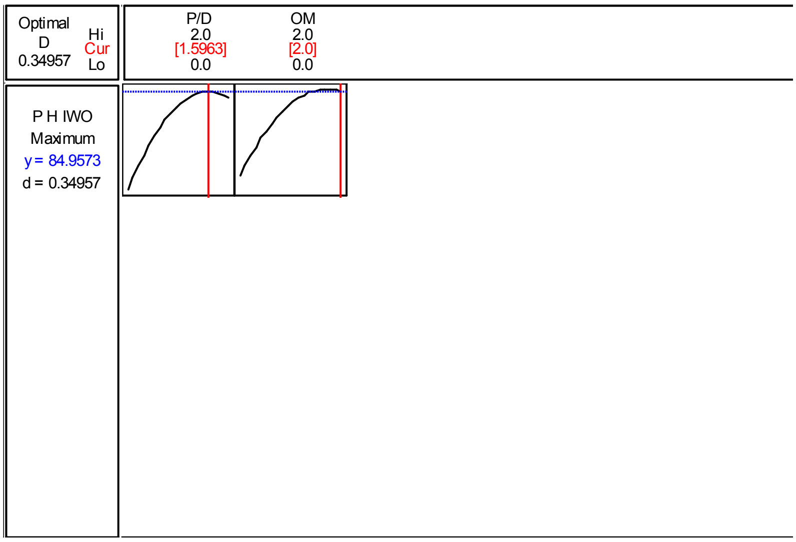

Figure H

The predicted optimum levels for Iwo station were obtained by applying response optimization and the levels were as follows: P/D = 1.596 (80kg/ha); OM = 2.00 (100kg/ha) with corresponding predicted response plant height 85.0cm.

4 Conclusion

RSM was performed to optimize the response variable. A first-order model uses low-order polynomial terms to describe some part of the response surfaces. Usually a first-order model fits the data by least squares. Once the estimated equation is obtained, an experimenter can obtain the ANOVA statistics (F-test, R^2, the adjusted R^2 and lack of fit), the contour plot, to determine adequacy of the fitted model. Lack of fit of the first-order model happens when the contour plot is not a plane. If there is a significant lack of fit of the first-order model, then a more highly structured model, such as second-order model may be studied in order to locate the optimum.

Based on the analysis carried out, the results show that 97.5 cm plant height could be produced by applying 85kg/ha of poultry-dung and 34kg/ha of organomineral in Apomu station. In Iwo station, 85.0cm plant height could be produced by applying 80kg/ha of poultry-dung and 100kg/ha of organomineral. 76.9cm plant height in Jago could be produced by applying 84kg/ha of poultry-dung and 52kg/ha of organomineral. Each location need different requirement of fertilizer application and all the locations need the average 83kg/ha of poultry-dung while Iwo location need as much as 100kg/ha of organomineral to produce the optimum plant height.

REFERENCES

[1] Bartlett, M.S. (1937), Properties of sufficiency and statistical tests. Proceedings of the Royal Statistical Society Series A 160, 268-282
[2] Box, E.P.George, Hunter, J. Stuart, and Hunter, G. William (2005), Statistics for Experiment. New Jersey: John Willey and Sons, Inc.
[3] Dean, Angela and Voss, Daniel. (1999), Design and Analysis of Experiments. New York: Springer.
[4] Douglas C. Montgomery (1976), Design and Analysis of Experiments. New York: John Willey and Sons, Inc.
[5] Iken, J.E. and Amusan, N.A. (March, 2004), Maize Research and Production in Nigeria. Journal of Agricultural Research. Vol.3(6) pp 302 - 307
[6] M. Carmen Ximénez y Rafael San Martín, (*2000),* Application of response surface methodology to the studyof person-organization fit. Psicothema, Vol. 12(1), pp. 151-158*,*
[7] Makinde, E.A. (2007), Effect of an Organo-mineral Fertilizer Application on the Growth and yield of maize. Journal of Applied Science Research. Vol. 16(1), pp 69 - 76
[8] Montgomery, Douglas C. (2005), Design and Analysis of Experiments: Response surface method and designs. New Jersey: John Willey and Sons, Inc.
[9] Myers, Raymond H. and Montgomery, Douglas C. (1995), Response Surface Methodology: the analysis of response surfaces, experimental designs for fitting response surfaces, 183-351. New York: John Willey and Sons, Inc.
[10] Raghavarao, D. and Myers, R. (1971), Statistical Design and Analysis of Industrial Experiment. Kluwer Academic Publisher
[11] Rao, C.R. (2004), An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publisher, Boston.