RESPONSE SURFACE OPTIMIZATION OF DIETARY IRON, CALCIUM AND VITAMIN C IN SOYAMILK FOR COMPLEMENTARY FEEDING

Abstract:

Response surface methodology (RSM) is a collection of tools developed in the 1950s for the purpose of determining optimum operating conditions. In this work, a three level three factor (3^3) factorial design that metamorphosed to the response surface design with two augmented central point was employed. In its applications a secondary data from the department of Food Science and Technology (FST), Michael Okpara University of Agriculture, Umudike (MOUAU), containing the mineral components of soymilk for complementary feeding of infants was used. The analysis for the First Order (FO), Two Way Interaction (TWI) and the Polynomial (PQ) model was carried out and the augmented response surface analysis was performed. Following the path of steepest ascent, an optimality condition from the surface and contour lines shows that dietary iron is significant for varying the colour content, while calcium was significant for varying the ash and moisture content. It was then recommended that for optimal colour content in the soymilk, 3.07mg/100ml of Dietary Iron, 154.1mg/100ml of Calcium and 24.23mg/100ml of Vitamin C should be used, for optimal ash content in the soymilk, 2.22mg/100ml of Dietary Iron, 152.03mg/100ml of Calcium and 13.53mg/100ml of Vitamin C should be used while for optimal moisture content in the soymilk, 2.9858mg/100ml of dietary Iron, 335.71mg/100ml of Calcium and 25.48mg/100ml of Vitamin C should be used.

Introduction

Response surface methodology is a procedure and a philosophy for the design, the conduct, the analysis, and the interpretation of experiments performed to determine the quantitative relationship between a dependent variable (the response) and one or more quantitative, continuous independent variables.

The basic approach, first suggested by Box and Wilson (1951), ingeniously combined elements of multiple regression theory and its specialized form in analysis of variance with special features of the factorial designs, including principles of partitioning, confounding and fractional replicates. The central composite design is one of a number of experimental designs developed specially for use in response surface exploration in order that the data collection phase be performed as completely, as cheaply and as efficiently as possible.

Box and Hunter (2005), suggested the characteristics of experimental designs for fitting response surfaces.

Naturally, Soymilk also known as vegetable or imitation milk is produced from whole soybean (glycine max).Soymilk resembles cow's milk in appearance flavor and nutritive value. When properly processed (Iwe, 2003) should contain 8.25% solid-not fat; not less than 3.25% fat, not more than 88.50% water and not less than 11.50% solids including 3.25% fat.

Soymilk or soy drink is a stable off-white emulsion/suspension water extract of whole soybean that contain 2% oil, 88% water, water soluble protein of about 3.5%, 2.9% carbohydrate, 0.5% ash and others like Calcium Iron Lecithin, Riboflavin, Isoflavones and Vitamin E. The protein content is higher than that of cow's milk by about 2.2%. Addition of Iron, Calcium and Vitamin C in foods including beverages like soymilk will not only meet the nutrient needs of infants and young children, but they also will work in synergy to promote growth performance (Clarke, 1995; Thiers, 2009). Among other sources of vegetable milk, soymilk had received very high research attention as reference vegetable milk (Onweluzo and Nwakalor, 2009).

Infancy is a period of tremendous physical growth characterize by increase in length and weight as well as physiological, immunological and mental development. Yeung, (2011). Furthermore, the composition of human milk varies in magnitude between nutrients in lactating mothers. Lonnerdal, (1985). These and more portend that with time (about 4-6 months to 12 months) the breast milk alone will not be sufficient to meet the child's nutrition for energy needs, it therefore becomes mandatory for an adequate and appropriate nutrition (in terms of calorie, vitamins and minerals) be introduced, else the infant will not achieve the expected growth. A complementary food is therefore introduced to improve both the energy and nutrient intakes since the child will no longer gain weight despite appropriate breast feeding, and will be feeling hungry always despite frequent breast feeding. Rarback, (2011). Some experimental analysis have been presented to ascertain these physio-chemical changes which include determination of PH, viscosity etc.

Factorial experiments are employed in all fields of life; agricultural science, biology, medicine, the physical sciences etc. experiments are usually carried out by researchers either to discover something about a particular process or to compare the effects of several factors on responses.

Factorial experiment is therefore a crossed factor design that usually involves several factors and it is such that every possible combination of the factor is included or observed or examined. Factorial experiment permits the analysis of a number of factors with the same precision (eg. Individual and joint effects) as if the entire experiment had been devoted to the study of only one factor.

Some notable factorial experiments are as follows;

2^k factorial experiments- This involves K factors each at two levels.

3^K factorial experiment- This involves K factors each at three levels.

B^K factorial experiment- This involves K factors each at B levels. (Montgomery 2013).

The problem:

According to Fallon and Enig (2007), Infants are at high risk of iron, protein and calcium deficiencies after six months of exclusive breast feeding. They stated that soymilk can serve as a supplement towards improving on these deficiencies. The problem now lies on determining the composition and quality of soymilk to be used. Furthermore, the composition and quality of soymilk varies with the variety of soybean used and the method of production (Wang et al., 1978). It is therefore necessary to statistically circumvent these problems.

The aim of this study is to apply response surface method in determining the optimal combination of levels of different component of soymilk as a complement for feeding infant after six months of exclusive breast feeding.

The specific objectives Include; To determine the optimal combinations of levels of the different component of soymilk (that is; Dietary Iron (Fe), calcium (Ca) & Vitamin C (C) that is suitable for complementary feeding in infants. To investigate the linear relationship as well as the curvature (quadratic) relationship using the response surface analysis. This study is going to help determine the combination of level of the different components of soymilk (that is; Dietary Iron (Fe) (X_1), calcium (Ca)(X_2) & Vitamin C (C) (X_3) that will be suitable for complementary feeding in infants, and would be a guide to people using this approach. This study is limited to the use of response surface methodology to analyze the different levels of the mineral components that made up soymilk for complementary feeding.

Methodology

The data used for this study are secondary data. It was gotten from the work "Application of response surface methodology to fortification of soymilk from sprouted soybean with Iron, Calcium and Vitamin C for complementary feeding" (FST), published by Dr. I. N. Okwunodulu (2014) from the department of Food Science and Technology, MOUAU.

RESPONSE SURFACE METHODOLOGY (RSM)- The method of response surface analysis was adopted for this study. However RSM has been reported to be the best option since it identifies the effects of the individual process variables, locates optimum process variable. Combinations for multivariable system efficiency, and offers economy of experimental points since it requires least experimental data. (Mullen and Ennia, 1979).

The objective of RSM experiments is to predict the value of a response variable called the dependent variable based on the controlled value of experimental factors called independent variables. As an important subject in the statistical design of experiment, the *Response surface methodology(RSM) is a collection of mathematical or statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response.*

A response surface is fitted an extension of linear model algorithm, and works almost exactly like it; however, the model formula for response surface must make use of the First Order, Two-Way Interaction, Pure Quadratic or Second Order models where the First Order model in (1.0) is given by:

$$y_{ijk} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon_{ijk} \quad (3.1).$$

Adding the interaction term introduces curvature into the response function. It is necessary to use more than two levels to detect curvature, however, and, in general, to determine the shape of the "response surface." That is, how does the response vary over different combinations of values of the factors? In what region(s), if any, is the change approximately linear? Are there humps, and valleys, and saddle points, and, if so, where do they occur? These are the types of questions that response surface methodology attempts to answer.

We usually represent the response surface graphically. To help visualize the shape of the response surface, we often plot the contours of the response surface. Each contour corresponds to a particular height of the response surface.

In most response surface methodology, the form of the relationship between the response and the independent variable is unknown. The first step in RSM is to find a suitable approximation for the true functional relationship between the set of independent variables. (Montgomery 2013).

RSA is based on the assumption that when k factors (or independent variables) are being studied in an experiment, the response (or dependent variable) will be a function of the levels at which these factors are combined (xk).

The Sequential Nature of the Response Surface Methodology

Most applications of RSM are sequential in nature.

Phase 0: At first some ideas are generated concerning which factors or variables are likely to be important in response surface study. It is usually called a **screening experiment**. The objective of factor screening is to reduce the list of candidate variables to a relatively few so that subsequent experiments will be more efficient and require fewer runs or tests. The purpose of this phase is the identification of the important independent variables.

Phase 1: The experimenter's objective is to determine if the current settings of the independent variables result in a value of the response that is near the optimum. If the current settings or levels of the independent variables are not consistent with optimum performance, then the experimenter must determine a set of adjustments to the process variables that will move the process toward the optimum. This phase of RSM makes considerable use of the first-order model and an optimization technique called the **method of steepest ascent (descent)**.

Phase 2: Phase 2 begins when the process is near the optimum. At this point the experimenter usually wants a model that will accurately approximate the true response function within a relatively small region around the optimum. Because the true response surface usually exhibits curvature near the optimum, a second-order model (or perhaps some higher-order polynomial) should be used. Once an appropriate approximating model has been obtained, this model may be analyzed to determine the optimum conditions for the process.

MATHEMATICAL MODEL EQUATIONS AND RSM MODEL SOLUTION SEARCH- RSM is often represented with mathematical models that resemble those of regression equations. These mathematical model equations are determined by the number of process variable cases involved and have the probability of showing significant/non-significant linear, quadratic and cross product (interaction) order effects. Those variables significant ($p>0.05$) at 1% level do not contribute at 5% level ($p\leq0.05$) (Bradley, 2007).

For two process variable cases, the mathematical model is;

$$y_{ijk} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_{12} + \varepsilon_{ijk} \qquad (3.2)$$

This model equation indicates significant/ non-significant two linear, two quadratic and a single cross product or interaction order effect.

The second-order model is widely used in response surface methodology for several reasons:

1. The second-order model is very flexible. It can take on a wide variety of functional forms, so it will often work well as an approximation to the true response surface.
2. It is easy to estimate the parameters (the β's) in the second-order model. The method of least squares can be used for this purpose.
3. There is considerable practical experience indicating that second-order models work well in solving real response surface problems.

For three process variable cases, the mathematical model is;

$$y_{ijk} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{12} x_{12} + \beta_{13} x_{13} + \beta_{23} x_{23} + \varepsilon_{ijk} \qquad (3.2.1)$$

This model equation indicates significant/ non-significant three linear, three quadratic and three cross product or interaction order effect.

Where; β_0= Intercept

B_i (ie. B_1, β_2, β_3)= linear regression terms

B_{ii} (ie. B_{11}, β_{22}, β_{33})= quadratic regression terms

B_{ij} (ie. B_{12}, β_{13}, β_{23})= cross product regression terms
ε= Random error term.
y_{ijk} = Dependent response variable

Normality, independent, homogeneity of variance assumptions were justified using the necessary approaches.

3.3 FACTORIAL DESIGNS (THE CCD'S WITH 5 AXIAL POINTS)

Factorial designs are designs in terms of treatment combinations (a factorial treatment design) which is a necessary first step in designing a factorial experiment after the factors and their levels are known. The central composite design is an experimental design, useful in response surface methodology, for building a second order (quadratic) model for the response variable without needing to use a complete three level factorial experiment and also for obtaining optimum conditions. The design consists of three distinct sets of experimental runs;

1. A factorial (perhaps fractional) design in the factors studied, each having two levels.
2. A set of center points, experimental runs whose values of each factor are the medians of the values used in the factorial portion. This point is often replicated in order to improve the precision of the experiment.
3. A set of axial points, experimental runs identical to the center points except for one factor, which will take on values both below and above the median of the two factorial levels and typically both outside their range. All factors are varied in this way.

The *central composite designs* (*CCDs*) are the most frequently used response surface designs. These designs permit the estimation of nonlinear effects and are constructed by starting with a two-level full factorial and then adding center points (i.e., at the center of the full factorial) and axial (star) points that lie outside the square formed from connecting the factorial points. The design for two factors is shown in Figure 12.7.The value of α would be selected by the experimenter. Desirable properties of the design include orthogonality and rotatability. A design is rotatable if $Var(y)$ is the same for all points equidistant from the center of the design. In the case of two factors, rotatability is achieved when α = 1.414. If there are not tight constraints on the number of center points that can be used, both orthogonality and rotatability can be achieved by selecting the number of center points to achieve orthogonality since the number of center points does not affect rotatability.

CCD enables estimation of the regression parameters to fit a second-degree polynomial regression model to a given response. A polynomial, as given by Equation (1.7), quantifies relationships among the measured response y and a number of experimental variables *X1…Xk*, where k is the number of factors considered, β are regressors and ε is an error associated with the model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \beta_{11} x_1^2 + \beta_{22} x_2^2 + ... + \beta_{kk} x_k^2 + \beta_{12} x_1 x_2 + ... + \beta_{k-1,k} x_{k-1} x_k + \varepsilon \qquad (3.9)$$

The regressors (β1, β2, β3…) in the various terms of Equation (3.9) provide a quantitative measure of the significance of linear effects, curvilinear effects of factors and interactions between factors. It is worth noting that the model presented by Equation (3.9) is not a model in purely physical sense, but rather it should be understood as a statistical model, *i.e.*, a correlation developed based on regression analysis.

However, this nomenclature is widely used in the field of design of experiments and statistics, and therefore it is used hereafter.

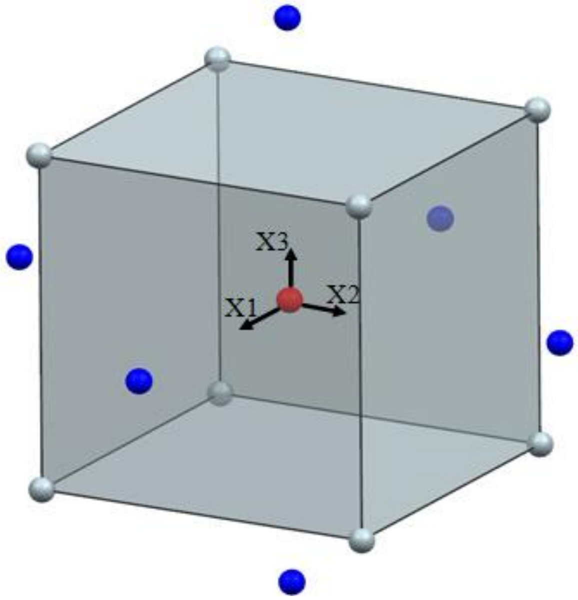

Figure 1.Visualization of original type rotatable CCD for 3 factors X1, X2 and X3

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Values at the center point (red point with coordinates 0, 0, 0) that is located in the center of the cube are used to detect curvature in the response, *i.e.*, they contribute to the estimation of the coefficients of quadratic terms. Axial points (six blue points located at a distance α from the center point) are also used to estimate the coefficients of quadratic terms, while factorial points (eight grey points located at corners of the cube with a side length equal to 2) are used mainly to estimate the coefficients of linear terms and two-way interactions. For testing four or more factors in an experiment, Figure 1 should be extended to the fourth or more dimensions (Marcin et al. 2015).

Wrong

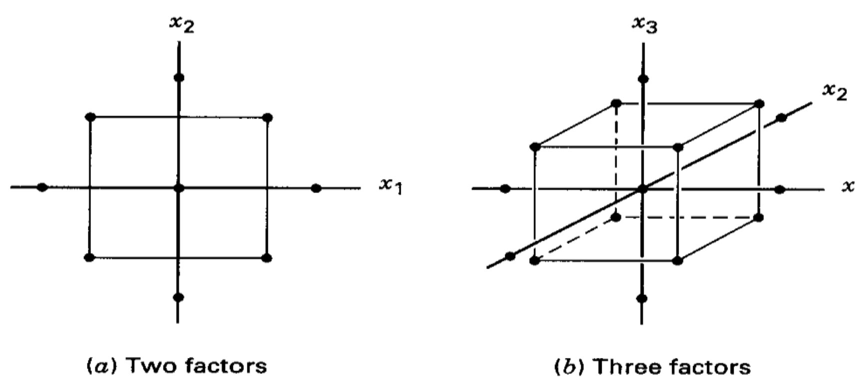


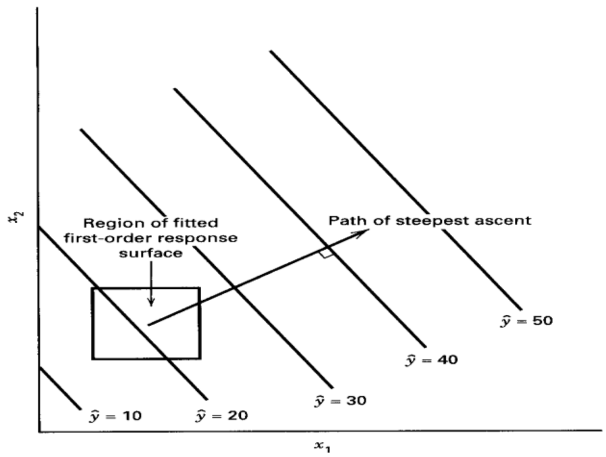
Figure 6-36 Central composite designs.

Fig 2 Composite design

3.4 THE METHOD OF STEEPEST ASCENT AND STEEPEST DESCENTS

The method of steepest ascent is a procedure for moving sequentially along the path of steepest ascent, that is, along the direction of maximum increase in the predicted response. The fitted first order model is; $y_{ijk} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$ (3.9.1)

And the fisrt order response surface, that is the contors of y, is a series of parrallel line such as that shown in figure 1.2 below. The direction of the steepest ascent is the direction in which y increases most rapidly. This direction is parallel to the normal to the fitted resonse surface. We usually take as the path of steepest ascent the line through the centre of the region of interest and normal to the fitted surface



Cite by?

Fig 3 Surface response

3.4.1 STEPS INVOLVED IN THE METHOD OF STEEPEST ASCENT

The following steps describe the general procedure:

1. The experimenter runs a first-order model =…………………. In some restricted region of variables, $X_1, X_2, \ldots, X_k$. The experiment usually contains center-points runs which can be used to perform a lack-of-fit test for curvature.
   (a) If a lack-of-fit for curvature is not significant, then go to step 2,
   (b) If lack-of-fit for curvature is significant and the experimenter is satisfied that little or no additional information can be obtained using the path of steepest ascent (or path of steepest descent) procedure, then we stop applying this method.
2. The fitted first-order model is used to determine a path of steepest ascent (or path of steepest descent).
3. A series of experimental runs is conducted along the path until no additional increase (or decrease) in response is evident.
4. Centered near the location along this path which yields a maximum (or minimum) response, a new experiment is designed.

5 Return to step 1.Once curvature is detected and the method is stopped, a more elaborate experiment to fit a quadratic response surface model should be designed and conducted.

3.5 METHOD OF STEEPEST DESCENT

The method of steepest descent is a procedure for moving sequentially along the path of steepest descent, that is, along the direction of maximum decrease in the predicted response. The steepest descent method, which is based on the gradient of $\varepsilon'\varepsilon$. Where;

$$\varepsilon'\varepsilon = [y - f(x,\Omega)]'[y - f(x,\Omega)] \quad (3.9.2)$$

Therefore, the gradient of $\varepsilon'\varepsilon$ is given by

$$\frac{\partial(\varepsilon'\varepsilon)}{\partial\Omega} = -2\left[\frac{\partial fx;\Omega}{\partial\Omega}\right]'[y - f(x;\Omega)] \quad (3.9.3)$$

STATISTICAL DATA ANALYSIS

```
>loveline.rsm(loveline.colour)
```

Where is the data?
The author did not apply step by step the theory that themselves copied from Montgomery book

It is not clear:

```
Call:
rsm(formula = response ~ SO(x1, x2, x3), data = data)

Estimate  Std. Error t value  Pr(>|t|)
(Intercept)  6.3046e-01  6.4155e-02  9.8271 3.869e-16 ***
x1           7.0659e-02  1.7460e-02  4.0468 0.0001058 ***
x2           2.4713e-02  1.7460e-02  1.4154 0.1602236
x3          -3.5846e-03  1.7460e-02 -0.2053 0.8377786
x1:x2        1.4804e-02  2.2814e-02  0.6489 0.5179860
x1:x3       -1.7857e-05  2.2814e-02 -0.0008 0.9993771
x2:x3       -1.3393e-03  2.2814e-02 -0.0587 0.9533113
x1^2         4.2221e-03  2.6226e-02  0.1610 0.8724430
x2^2        -3.3269e-03  2.6226e-02 -0.1269 0.8993217
x3^2        -1.8299e-02  2.6226e-02 -0.6977 0.4870454
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.1734,    Adjusted R-squared:  0.09504
F-statistic: 2.214 on 9 and 95 DF, p-value: 0.02754

Analysis of Variance Table

Response: response
```

```
Df   SumSq  Mean Sq F value    Pr(>F)
FO(x1, x2, x3)    3 0.53696 0.178986  6.1407 0.0007324
TWI(x1, x2, x3)   3 0.01237 0.004124  0.1415 0.9348720
PQ(x1, x2, x3)    3 0.03135 0.010451  0.3586 0.7830624
Residuals        95 2.76901 0.029148
Lack of fit       5 0.08953 0.017905  0.6014 0.6989489
Pure error       90 2.67949 0.029772

Stationary point of response surface:
         x1          x2          x3
-3.03525471 -3.04171908  0.01484657

Eigenanalysis:
$values
[1]  0.008760942 -0.007830431 -0.018334097

$vectors
          [,1]        [,2]        [,3]
x1  0.85241769  0.52258593 -0.01697144
x2  0.52269438 -0.85087586  0.05292317
x3 -0.01321631  0.05398353  0.99845436
```

RESULT- The result shows that in the first order model, only the and X_2 variables are significant while the variable X_3 is not significant. The second-order model and the polynomial terms show no significance Who are X1, X2, X3?

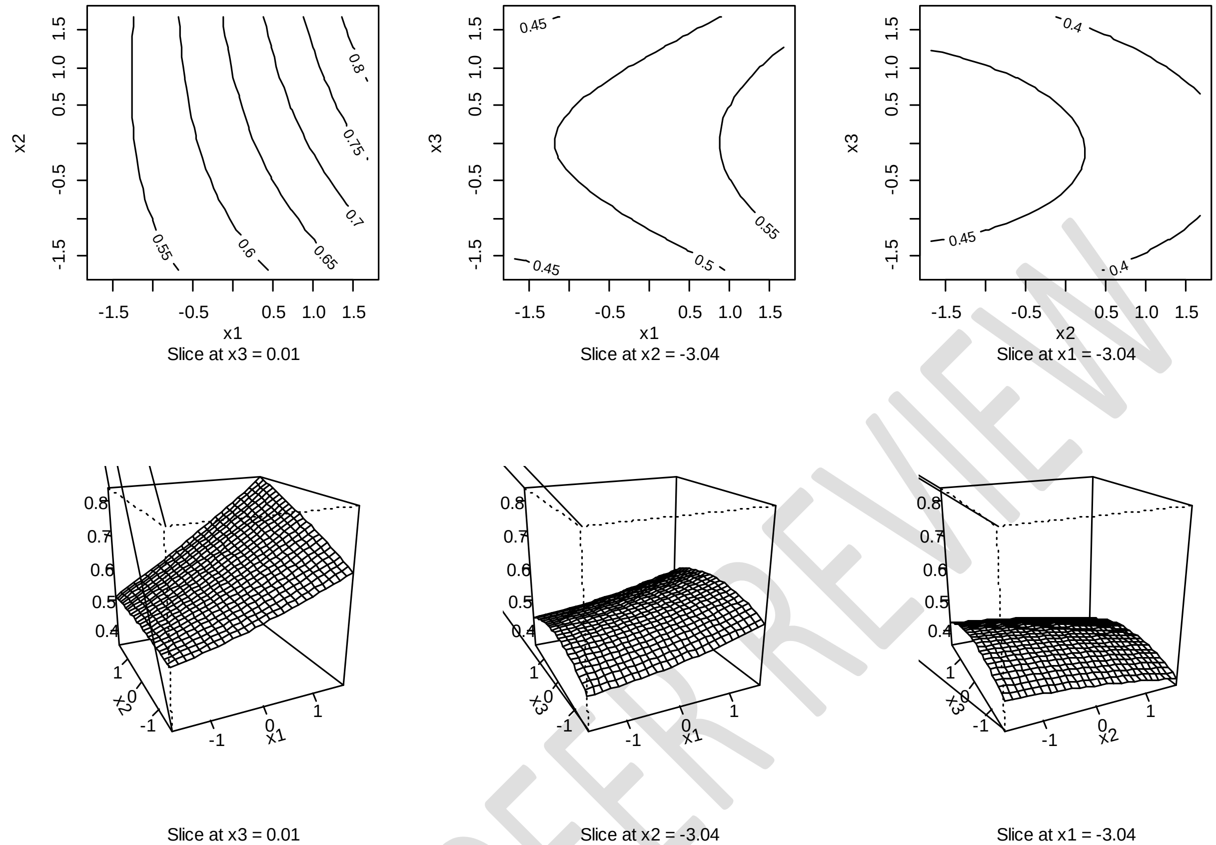


FIGURE 4. The response surface plots of the colour content.
Explain!


```
>loveline.rsm(loveline.ash.content)

Call:
rsm(formula = response ~ SO(x1, x2, x3), data = data)

Estimate  Std. Error t value Pr(>|t|)
(Intercept)  3.5825e-02  8.0072e-04 44.7405   <2e-16 ***
x1           8.3194e-05  2.1792e-04  0.3818   0.7035
x2           9.2780e-03  2.1792e-04 42.5743   <2e-16 ***
x3          -8.4156e-05  2.1792e-04 -0.3862   0.7002
x1:x2        1.7857e-05  2.8475e-04  0.0627   0.9501
x1:x3        1.2500e-04  2.8475e-04  0.4390   0.6617
x2:x3        1.7857e-05  2.8475e-04  0.0627   0.9501
x1^2         7.7611e-05  3.2733e-04  0.2371   0.8131
x2^2        -4.8627e-05  3.2733e-04 -0.1486   0.8822
x3^2        -2.7585e-04  3.2733e-04 -0.8428   0.4015
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared:  0.9503,    Adjusted R-squared:  0.9455
F-statistic: 201.6 on 9 and 95 DF,  p-value: < 2.2e-16

Analysis of Variance Table

Response: response
Df    Sum Sq    Mean Sq  F value Pr(>F)
FO(x1, x2, x3)   3 0.0082314 0.00274379 604.2883 <2e-16
TWI(x1, x2, x3)  3 0.0000009 0.00000030   0.0669 0.9774
PQ(x1, x2, x3)   3 0.0000076 0.00000252   0.5560 0.6453
Residuals       95 0.0004314 0.00000454
Lack of fit      5 0.0002948 0.00005896  38.8516<2e-16
Pure error      90 0.0001366 0.00000152

Stationary point of response surface:
         x1          x2          x3
0.11176619  0.02034834 -0.65457617

Eigen analysis:
$values
[1]  0.0000000000  0.0000000000 -0.0002868042

$vectors
         [,1]        [,2]        [,3]
x1 0.98259047  0.07883062  0.16823108
x2 0.07472136 -0.99673398  0.03062844
x3 0.17009609 -0.01752476 -0.98527164
```

RESULT- The result shows that only the first-order variables, X1 and X3 show significance while the second-order and the polynomial terms show no significance. ??

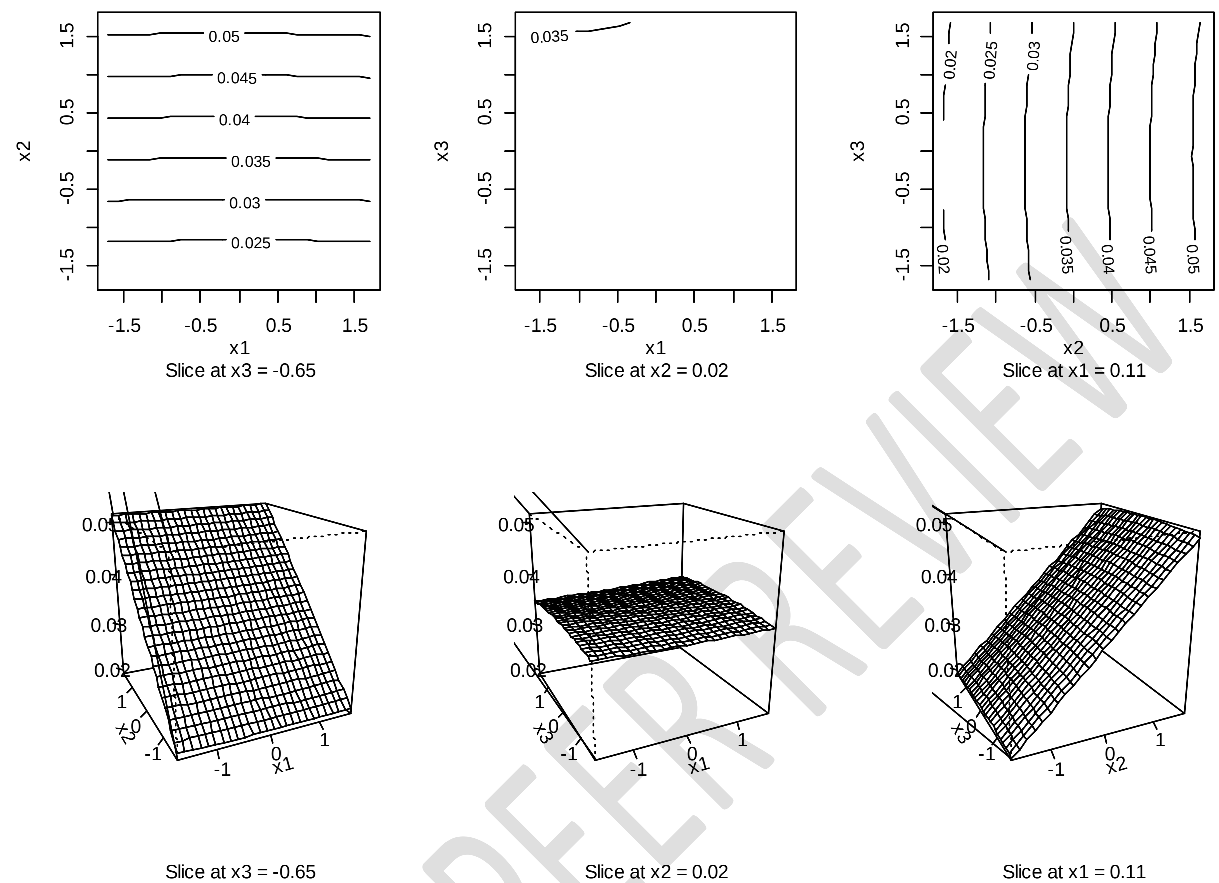


FIGURE 5 RESPONSE SURFACE PLOTS OF ASH CONTENT

EXPLAIN

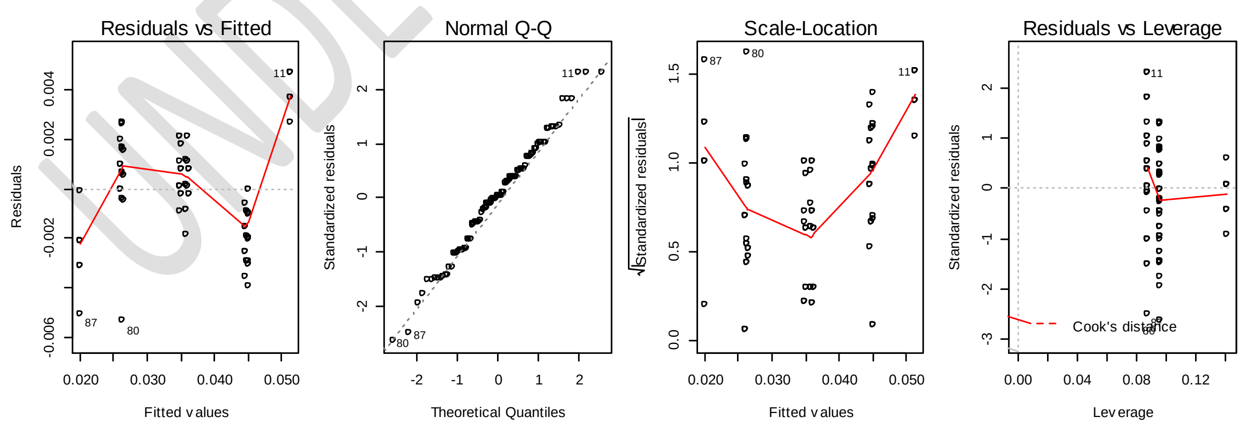


FIGURE 6 THE RESIDUAL ANALYSIS PLOTS OF THE ASH CONTENT

EXPLAIN

For Moisture:

```
loveline.rsm(loveline.Moisture.new)

Call:
rsm(formula = response ~ SO(x1, x2, x3), data = data)

              Estimate Std. Error  t value  Pr(>|t|)    
(Intercept) 95.6709049  0.2109203 453.5879 < 2.2e-16 ***
x1          -0.0013597  0.0574040  -0.0237    0.9812    
x2          -0.4239059  0.0574040  -7.3846 5.827e-11 ***
x3          -0.0013361  0.0574040  -0.0233    0.9815    
x1:x2        0.0016071  0.0750057   0.0214    0.9830    
x1:x3       -0.0044643  0.0750057  -0.0595    0.9527    
x2:x3       -0.0055357  0.0750057  -0.0738    0.9413    
x1^2         0.0532441  0.0862217   0.6175    0.5384    
x2^2         0.1350463  0.0862217   1.5663    0.1206    
x3^2         0.0540016  0.0862217   0.6263    0.5326    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Multiple R-squared:  0.3762,    Adjusted R-squared:  0.3171 
F-statistic: 6.365 on 9 and 95 DF,  p-value: 5.071e-07

Analysis of Variance Table

Response: response
Df  Sum Sq Mean Sq F value    Pr(>F)
FO(x1, x2, x3)   3 17.1807  5.7269 18.1779 2.111e-09
TWI(x1, x2, x3)  3  0.0030  0.0010  0.0031    0.9998
PQ(x1, x2, x3)   3  0.8649  0.2883  0.9151    0.4367
Residuals       95 29.9296  0.3150                  
Lack of fit      5  1.5406  0.3081  0.9768    0.4364
Pure error      90 28.3890  0.3154                  

Stationary point of response surface:
          x1           x2           x3 
-0.007064507  1.571423533  0.092622320 

Eigen analysis:
$values
[1] 0.13515019 0.05579973 0.05134208

$vectors
          [,1]        [,2]       [,3]
x1  0.01074151 -0.65155400 0.75852621
x2  0.99935104  0.03307746 0.01426082
x3 -0.03438182  0.75788078 0.65148647
```

RESULT- The result shows that only the first-order variables X1 and X2 show significance while the second.-order and the polynomial terms show no significance
EXPLAIN

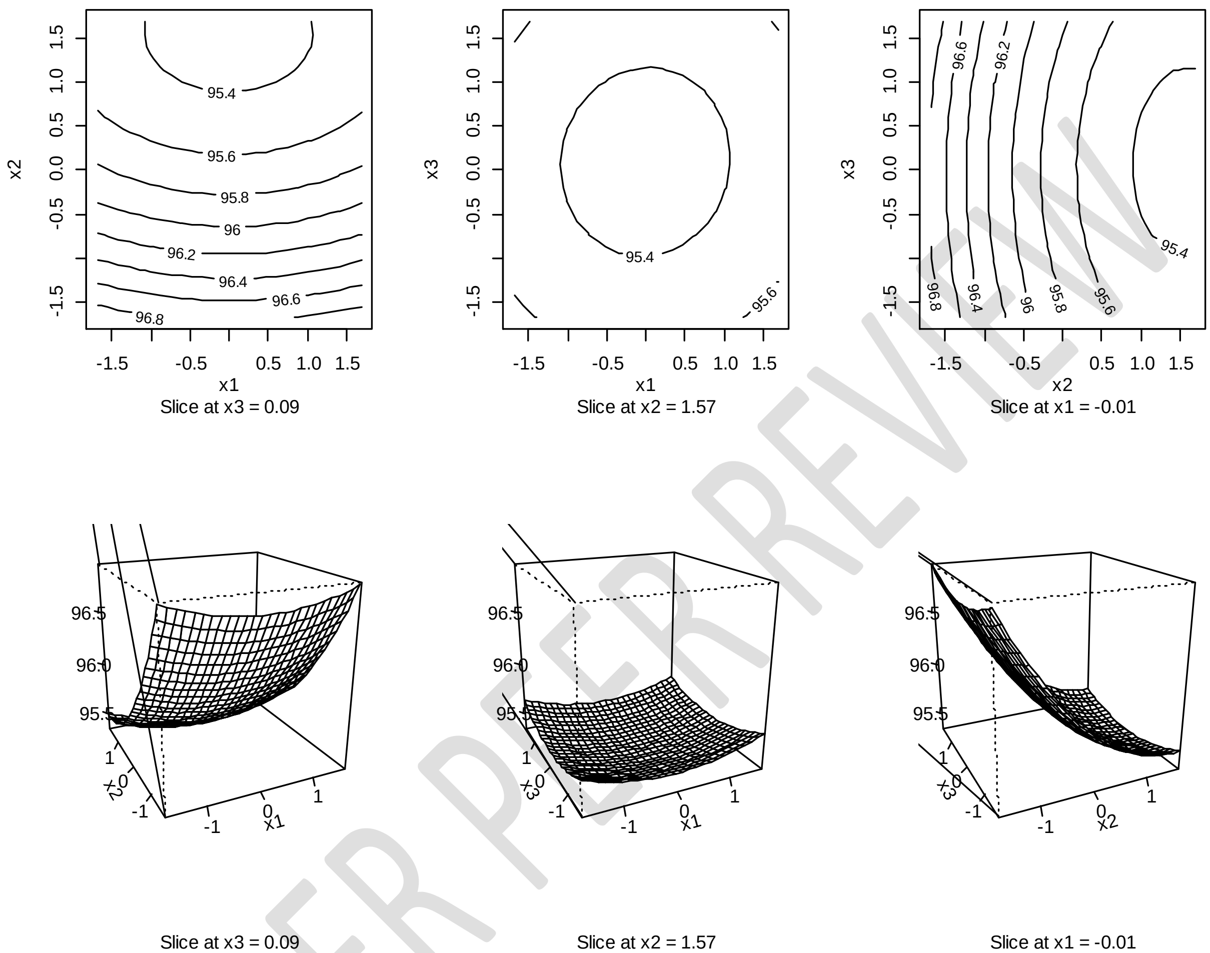


FIGURE 7 RESPONSE SURFACE PLOTS OF THE MOISTURE CONTENT EXPLAIN

Diagnostics:

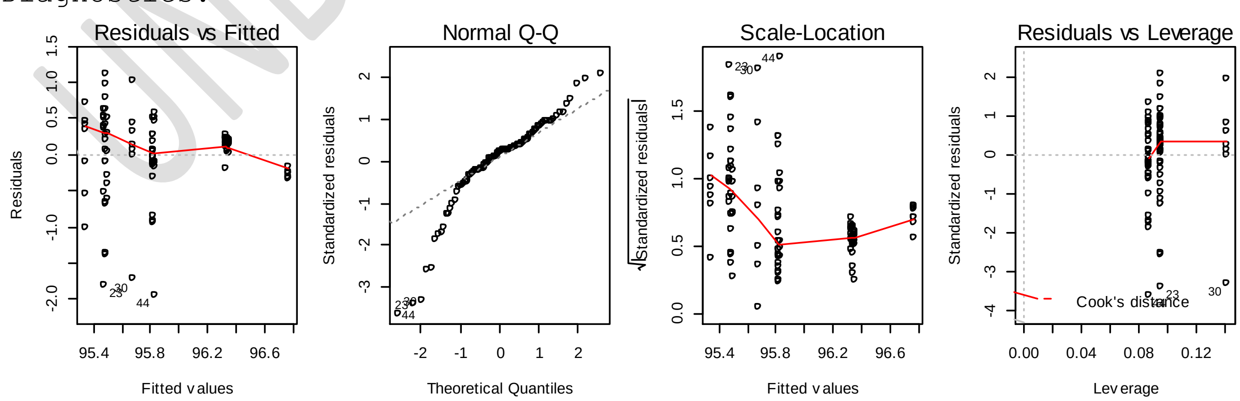


FIGURE 8 RESIDUAL ANALYSIS PLOTS OF THE MOISTURE CONTENT

CONCLUSION

The objective of this study is to determine the optimal combinations of levels of the different minerals (for soymilk) that is suitable for complementary feeding, and also to investigate the linear relationship as well as the curvature (quadratic) relationship using the response surface analysis.

As soon as we are close to the optimum a rotatable central composite design can be used to estimate the second-order response surface. The optimum on that response surface can be determined analytically.

Results in this study indicated that only the first-order process variables had significant ($P < |t|$).

The second-order process variable and the polynomial process variables show non-significance. Response surface analysis of the experimental data on colour content located maximum point for X1 at -3.04, X2 at -3.04 and X3 at 0.01, for the ash content, the maximum point for X1 was at 0.11, X2 at 0.02 and X3 at -0.65, while for the moisture content, the maximum point for X1 was at -0.01, X2 at 1.57 and X3 at 0.09.

RECOMMENDATIONS

In order to raise healthy infants using Soymilk as a complement to breast milk, the following recommendations are made;

(i) Colour content of Soymilk with the mixture compositionsX1at -3.04, X2 at -3.04 and X3 at 0.01 should be encouraged for feeding infants and young children.

(ii) Ash content of Soymilk with the mixture compositions X1 at 0.11, X2 at 0.02 and X3 a t -0.65 should be encouraged for feeding infants and young children.

(iii) Moisture content of Soymilk with the mixture compositions X1 at -0.01, X2 at1.57 and X3 at 0.09 should be encouraged for feeding infants and young children.

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