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Predictive Modeling and Optimization of Extrusion Cooking Process for Color Characteristics and Consumer Acceptability of Fortified Rice Snacks

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Abstract: *Production of extruded snacks from different blends of low grade milled rice and cowpea flours was conducted and extrusion parameters were optimized using response surface methodology (RSM) and desirability function. A 3-factor, 5-levels central composite rotatable design was employed to determine the effect of the process parameters, namely temperature (100-140^{o}C), feed moisture (15-25%) and cowpea composition (8-24%) on colour indices and consumer acceptability. Total of 20 extrusion experiments were performed and data fitted to a second-order polynomial equation through regression analysis. Results showed satisfactory fit of the data with coefficient of determination (R^2) values of 0.9660, 0.9840 and 0.9520 for L*, a* and b* colour characteristics respectively and non-significant (p>0.05) lack-of-fit test. The optimum conditions of extrusion conditions were: temperature 120^{o}C, 20% moisture and 24% feed cowpea composition which corresponds to optimal L* =16.16, a* = 2.06 and b* = 22.16 recorded from combined desirability function of 0.9940. The acceptability test indicated that the snack produced at the optimal temperature (120^{o}C) containing the least cowpea composition (2.6%) and extruded at 20% moisture content was highly rated 9.88 on a 15 point scale. Principal component analysis of colour and sensory data shows that the first five principal components (PCs) contributed up to 94.9% of the total variations observed, with PC_1 contributing 30%, PC_2 responsible for 23.8%, PC_3 provides 17.3%, while PC_4 and PC_5 contributing 15.5 and 8.1% respectively. Thus demonstrating adequacy of RSM model and desirability function to predict optimal process conditions and consumer acceptability.*

***Keyword**: Rice, extrusion, RSM, optimization, snacks, colour, acceptability*

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I. Introduction

Extrusion cooking (EC) is a high temperature short time (HTST) process which has been used extensively in the cereal industry to produce breakfast cereals, snacks, baby foods, pasta products, extruded bread, beverages powders, textured vegetable protein, and several other puffed foods (Abd El-Hady *et al*., 1998; Danbaba *et al*, 2016). These products are principally attractive to consumers because of their diversity in composition, shapes, puffed texture and colour characteristics (Chakraborty *et al*, 2014).

Colour in extruded food, just like in most foods products acts as a trigger force for acceptance by consumer, and change in colour during processing may also indicate nutrient degradation (Bjorck and Asp, 1984; Nisha, *et al*., 2004). Bhattacharya *et al.* (1997) reported that during HTST cooking, because of the variability in chemical and physical characteristics of the raw materials, high temperature, short residence time and low moisture, there is significant impact on the colour characteristics of the extruded foods. Chakraborty *et al*, (2014) attributed the changes in colour principally to pigment degradation and non-enzymatic browning reactions favoured by HTST process conditions.

In some baked or fried products such as bread and biscuits, development of brown crust are desirable and greatly impact consumer overall acceptability (Chakraborty *et al*, 2014), but in extruded foods, colour development have been used as an indication of nutrient degradation and consumer acceptability (Nisha, *et al*., 2004). Apart from change in colour, other changes observed during HTST cooking include starch gelatinization (Akdogan, 1999), protein denaturation (Iwe *et al*., 2003), and vitamin and pigments degradation (Ilo *et al*, 1999) and mineral changes (Danbaba *et al*, 2015). These changes often resulted in new product with new physical, functional, nutritional, surface colour characteristic and overall acceptability (Bryant, *et al*., 2001). Several workers including Moore *et al*., (1990), Abd El-Hady *et al*., (1998), Akdogan (1999), Iwe *et al*., (2003), Filli *et* *al*., (2010, 2013) and Danbaba *et al*, (2013, 2016, 2017) have developed food products from cereal-based raw materials using HTST cooking technology and reported the need for a systematic evaluation of extruder variable settings to achieve the desired quality of finished product.

Most studies aimed at understanding and optimizing transformations taking place in the extruder during EC process have used response surface methodology (RSM). This is majorly because RSM approach allows the experimenter to establish mathematical model which explians the relationship between multiple input (extruder) variables and response (product) variables and therefore give a close to perfect conditions at industrial scale. Also, results of the application of RSM and designed experiment are very useful and practical, though its applicability has been limited to the scope of specific investigation because of variation in raw materials quality attributes. RSM has also been demonstrated to be an effective technique to model process conditions while minimizing the number of variables. The application of RSM therefore, involves three major steps: performing statistically designed experiments, estimating the coefficients in a mathematical model and predicting the response and checking the adequacy of the model (Sadhukhan *et al*., 2016). The application of mathematical modelling techniques for new food product development or improvement is fast increasing especially where new raw materials and technology is to be adopted (Granato *et al*, 2010). Tiwari *et al*, (2008) used RSM based on central composite design (CCD) to determine and optimal processing variables for colour development in fruit juice, and reported that the model fitted for the prediction of colour characteristics were closely correlated to the experimental results and non significant lack-of-fit.

Desirability analysis on the hand is applied in numerical process optimization where desired goal for each variable and responses are first defined and goals set (to maximize, minimize, keep within target, within range, none) for responses variables and exact value factors independent variables. In this approach, minimum and maximum levels are provided for each input or response variables being considered. A weight can then be assigned to each goal to adjust the shape of its particular desirability function and finally, the goals are combined into an overall desirability function. Desirability function is an objective function that ranges from 0 (outside of the limits), to 1 (at the goal). The program therefore seeks to maximize this function (Chattoraj, *et al*., 2014; Sadhukhan *et al.*, 2016).

Quantitative descriptive analysis (QDA) technique has gained greater acceptance in evaluating new product acceptance by consumers, because trained panelists are given the opportunity to subjectively measures specific quality characteristics of a product to yield a comprehensive qualitative product description suitable for statistical analysis (Stone and Sidel, 1998; Chapman *et al*, 2001; Danbaba *et al*, 2017). In this study, RSM and desirability function (DF) were used to investigate the colour changes during EC using twin-screw extruder for rice-cowpea blends at different levels barrel temperature (X_1), feed moisture content (X_2) and rice-cowpea ratio (X_3), keeping other extruder variables constant. Predictive regression models were fitted for the colour parameters and used to determine the optimum process conditions. Consumer preference analysis of the rice-cowpea snacks was also conducted using QDA to assess the impact of colour change on consumer preference.

II. Materials And Methods

Materials: The snacks were manufactured from blends of raw milled rice (*Oryza sativa* L) and cowpea (*Vigna unguiculata*). FARO 44, an improved high amylose (29.38±0.7%) lowland rice variety cultivated during the 2014 cropping season was obtained from the Breeding Laboratory of Rice Research Program, National Cereals Research Institute (NCRI), Badeggi, while cowpea (Ife brown) was bought from Bida main market, Nigeria. Milled rice and decorticated cowpea were manually cleaned and ground into flour using attrition mill (locally fabricated) and passed through International Standard 200 mesh sieve and the under flow were collected and stored in a covered plastics containers prior to extrusion and analysis.

Experimental design and outline: RSM in a central composite rotatable design (CCRD) consisting of three independent variables, X_1), X_2 and X_3 at five levels (+1.682, +1, 0, -1, -1.682) (Table 1) were used for this experiment. This approach reduces the number of experimental runs and suitable for process optimization involving more than two independent variables. The number of experiments (N) for CCRD was estimated using the relationship: $N = 2^n + 2n + n_c$, where 2^n is the factorial points with its origin from the centre point, 2n is the axial points, n_c is the number of centre points that provide replicates of the tests at the centre and square terms generated by from the centre at a distance α (±1.6817) (Fig. 1). With these three variables and addition of 6 centre points, $N = 2^3 + (2x3) + 6 = 20$ (Table 2). The addition of the 6 centre points was to minimize the effects of unexplained variability in the response variables due to extraneous factors (Chakraborty *et al*, 2014). Preliminary experiments were conducted and X_1, X_2 and X_3 were set between 100 – 140°C, 25g water/100 g sample and 8 – 24 g cowpea/100g rice flour respectively (Table 1). The low, center and high levels of each independent variable are coded as -1, 0 and +1 respectively as presented in Table 1 using the coding transformation according to the following equation:

$$x_i = \frac{X_i + X_0}{\Delta X_i} \qquad (1)$$

where x_i is the dimensionless value of the independent variables, X_i is the natural value of the independent variable, X_o is the real value of an independent variables at the centre point (0) and ΔX_i is the change in step of the natural value of variables *i* which correspond to a change of a unit of the dimensionless value of the variable *i*.

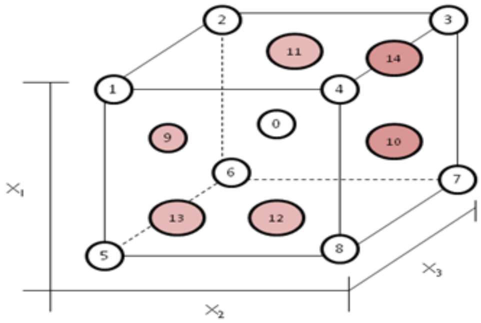

Figure 1: Schematic presentation of location of points in a 2^3 factorial design (8 factorial points with its origin from the centre point, 6 axial points, and 6 centre points)

Table 1: Independent variables and their natural levels for the central composite rotatable design

Variables	Unit	Symbol	Levels of coded variables				
			-α	Low	Medium	High	+α
			-1.6817	-1	0	1	+1.6817
Barrel temperature	^oC	X_1	86.0	100.0	120.0	140.0	154.0
Feed moisture	g/100 g	X_2	11.6	15.0	20.0	25.0	28.4
Rice-cowpea ratio	g/100 g	X_3	2.6	8.0	16.0	24.0	29.5

Level of each variable was established based on a preliminary extrusion. The distance of the axial points from the centre point was ± 1.68, and calculated from Equation α = (2n)1/4 where n is the number of variables.

Snack production: The rice and cowpea flours were formulated based on the experimental design (Table 2) and consist of 2.6, 8.0, 16.0, 24.0 and 29.5 g cowpea/100 g rice flour and the initial moisture contents determined by the standard dry oven method (AOAC, 1984). The moisture contents were adjusted to 11.6, 15.0, 20.0, 25.0, and 28.8% (wb) by adding specific amount of water according to the relationship: $y = (M_f - M_i) \times W_s \div (100-M_f)$, where y is the amount of water to be added (mL), M_f = intended final moisture content, M_i = initial moisture, W_s = sample weight (g) (Danbaba *et al*., 2015). The blends with specific moisture content and blending ratios were processed by manually feeding (300 g/min) into a conical hopper at a speed of 30rpm speed in a co-rotating twin-screw extruder (SLG 65, Jinan Saibaino Techn. Dev. Co. Ltd, China) with a constant screw geometry and 20 equidistance positioned flight. The barrel temperature was set and maintained by an in-build thermostat and control unit at 86, 100, 120, 140 and 154^{o}C. Samples of extruded snacks were collected once a steady state was achieved (Likimani *et al*., 1991; Filli *et al*., 2011). Extruded snack samples were collected and dried before subjecting to colour and consumer acceptability analysis.

Table 2: Outline of experimental design points with independent variables in their coded and un-coded forms based on the RSM and CCRD

Runs	Independent variables in coded form				Independent variable in its natural form		
	X_1	X_2	X_3		Barrel temperature (X_1, ^{o}C)	Feed moisture content (X_2, g/100g)	Feed cowpea composition (X_3, g/100g)
1	-1	-1	-1		100	15	8
2	1	-1	-1		140	15	8
3	-1	1	-1		100	25	8
4	1	1	-1		140	25	8
5	-1	-1	1		100	15	24
6	1	-1	1		140	15	24
7	-1	1	1		100	25	24
8	1	1	1		140	25	24
9	-1.6817	0	0		86.36	20	16
10	1.6817	0	0		153.64	20	16
11	0	-1.6817	0		120	11.59	16
12	0	1.6817	0		120	28.41	16
13	0	0	-1.6817		120	20	2.55

14	0	0	1.6817		120	20	29.45
15	0	0	0		120	20	16
16	0	0	0		120	20	16
17	0	0	0		120	20	16
18	0	0	0		120	20	16
19	0	0	0		120	20	16
20	0	0	0		120	20	16

Repeated measurements were carried out at all design point and mean recorded. Run 15 were repeated 6 times and the experimental runs randomized.

Colour determination: The colour measurements were determined on pulverized samples and estimated based on the International Commission on Illumination (CIE, 1976) L*, a*, b* method which is often used in food research using Monilta Colour Reader CR-10 (Minolta Co. Ltd., Tokyo, Japan). The equipment was standardized with a white square, which had standards of L = 98.97, a = +0.04 and b = +1.69. In the CIE-Lab scale, $L*$ represent lightness, $a*$ for (+) redness and (–) greenness, and $b*$ for (+) yellowness and (–) blueness, accordingly. Ten (10) measurements were taken for each sample.

Consumer Acceptability Test: Twenty five (25) semi-trained panellists from the Staff of NCRI, Badeggi, comprising of 21 women, 4 men with age between 28 – 43 years were recruited for sensory evaluation of the extruded snacks. Qualitative descriptive analysis (QDA) was used where panelists work together in a focus group to identify key product attributes and appropriate intensity scales specific for the products. These groups of panelists are then trained to reliably identify and score product attributes repeatedly. Quality attributes were quantified with an intensity scale from 0 to 15, where 0 = poor attribute rating and 15 extremely strong rating. The attributes evaluated were colour, aroma, flavour, texture, mouth field and overall acceptability. Panellist evaluated individually, the samples presented in a covered 20 ml plastic containers which was labelled with a three digit code and samples presented at room temperature (30±2^{o}C). Three samples each were evaluated by panellist per season and were given mineral water and unsalted cracker biscuits to clean their palate between each test. Overall acceptability rating was then measured with a scale of 1 to 15 where less than 4 were considered poor rating, 4-7 was fair and greater than 7 was high rating. QDA results were analyzed statistically and graphically.

Desirability function analysis: Desirability function approach through numerical optimization was carried out on the mean responses to simultaneously determine the optimum settings of the independent variables that can determine the optimum levels of one or more responses. These procedures were carried out in two stages: (1) each response (y_i) was first converted into individual desirability function (d_i) which varies over a range of $0<d_i<1$ and (2) all desirability were summed into a composite desirability which forms a single desirability function (Eqn. 3) where y_i is at required target or goal, d_i = 1, and where the response is outside an acceptable region, d_i = 0. Then the design variables are chosen to maximize the overall desirability.

$$D = (d_1 x d_2 x \dots \dots . d_n)^{1/n} \tag{3}$$

Depending on the desire of the experimenter of whether a response variable y_i is to be minimized, maximized or assigned a target value, the desirability function $d_i(y_i)$ was determined based on the proposal of Derringer and Suich, (1980). If an individual response variable is to be minimized, the individual desirability (d_i) is calculated as:

$$\begin{cases} d_i = 1, if\ y_i \leq T_i \\ d_i = 0, if\ y_i \geq U_i \\ d_i = [(y_i - U_i) \div (T_i - U_i)]^q, if\ T_i \leq y_i \leq U_i \end{cases} \tag{4}$$

If response is to be maximized, then

$$\begin{cases} d_i = 0, if\ y_i \leq L_i \\ d_i = 1, if\ y_i \geq T_i \\ d_i = [(y_i - L_i) \div (T_i - L_i)]^q, if\ L_i \leq y_i \leq T_i \end{cases} \tag{5}$$

But, when the response variable is to be kept within "target" range, then its individual desirability function is:

$$\begin{cases} d_i = 1, if\ y_i = T_i \\ d_i = 0, if\ y_i = L_i\ or y_i = L_i \\ d_i = [(y_i - L_i) \div (T_i - L_i)]^q, if\ L_i \leq y_i \leq T_i \\ d_i = [(y_i - U_i) \div (T_i - U_i)]^q, if\ L_i \leq y_i \leq T_i \end{cases} \tag{6}$$

where d_i is the desirability function, while L_i, U_i and T_i are the lower, upper and target values respectively that are desired as response (y_i), with $L_i \leq y_i \leq U_i$. The overall desirability function therefore was calculated using the Numerical Response Optimizer of Minitab statistical software version 14.13 (Mintab Inc, 2004).

Statistical analysis and model fitting: As required in the application of RSM and CCRD, data generated for the responses were fitted to a mathematical model and subsequently, optimum levels of the dependent and independent variables that satisfy optimal conditions were simultaneously located through numerical optimization (Khuri and Cornell, 1987; Chakraborty *et al*, 2014). The experimental data for all the response variables were fitted to a second order polynomial equation (7) to show the relationship between the response and independent variables.

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_I + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \sum_{i=1}^{n=1} . \sum_{j=i=1}^{n} \beta_{ij} X_i X_j \quad (7)$$

where Y is the response, *n* is number of independent variables and X are the variables, while β_o, β_i, β_{ii} and β_{ij} are the regression coefficients of the model, linear, square and interaction respectively. The model adequacy was evaluated using model analysis, lack-of-fit test, R^2 (coefficient of determination) analysis. A model is said to be adequate to describe the observed response if the R^2 and adjusted R^2 (R^2_{adj}) are more than 80% and coefficient of lack-of-fit is insignificant (Chakraborty *et al*, 2014). The statistical validity of the model was tested through analysis of variance (ANOVA) and significance considered at 5% level of probability. Numerical optimization was also carried out to locate optimum levels of the combination of the response and independent variables using statistical software (Minitab version 16). Principal component analysis (PCA) was applied with factor analysis on the QDA data (Lawless and Heymann, 1998).

III. Results and Discussion

RSM analysis of colour development in rice-cowpea snacks

Lightness (L*): The term lightness or brightness refers to the relationship between reflected and absorbed light, regardless of specific wavelength. The values range from 0 (absolute black) to 100 (pure white) (Peas and Maga, 2004). The effects of the process variables on the colour characteristics of extruded snacks are presented in Table 3. Perusal through the results indicated that sample containing 24% cowpea flour and extruded at 120°C and moisture level of 25% recorded the lowest extrudate lightness value of 11.45, while sample with the same cowpea composition but extruded at higher temperature (140°C) and lower moisture level (15%) recorded the highest L* value of 21.32, indicating significant ($p \leq 0.05$) variation in brightness of extruded snacks due to difference in extrusion conditions. Increasing temperature from 120°C to 140°C and reduction of moisture from 25 to 15% may be responsible for the reduction in product lightness. Bhattacharya *et al.* (1997) reported that during HTST cooking, the chemical composition of the raw materials, high temperature above 120°C and increased residence time inside the extruder due to low moisture level have significant impact on the colour of the extruded products. The changes in colour properties were attributed primarily to non-enzymatic browning favoured by extrusion conditions. In this study, the variation in L* colour index indicates that as the cowpea content increases from 16% to 24% and extrusion temperature from 120 to 140°C, there was clear darkening of extruded snack.

Table 3: Experimental design matrix for the preparation of rice-cowpea snacks using CCRD and RSM and colour responses variables

Runs	Independent variables				Colour characteristics							
					L*			a*			b*	
	X_1	X_2	X_3		OBS	PRD		OBS	PRD		OBS	PRD
1	100	15	8		13.14	13.29		0.70	0.67		18.36	17.93
2	140	15	8		13.13	12.78		1.66	1.39		21.00	21.80
3	100	25	8		18.89	18.71		0.56	0.57		17.83	17.81
4	140	25	8		14.01	14.13		1.80	1.77		24.52	25.22
5	100	15	24		20.06	19.79		2.46	2.43		20.36	20.03
6	140	15	24		21.32	21.34		1.78	1.71		20.33	20.72
7	100	25	24		13.46	13.66		0.68	0.69		19.00	18.56
8	140	25	24		11.45	11.14		0.50	0.46		22.00	22.79
9	86.4	20	16		16.70	16.69		1.12	1.11		16.00	16.90
10	153.6	20	16		13.90	14.14		1.42	1.52		25.13	23.71
11	120	11.6	16		15.66	15.86		1.53	1.62		18.73	18.65
12	120	28.4	16		11.81	11.84		0.48	0.48		20.73	20.29
13	120	20	2.6		15.37	15.45		1.00	1.05		23.52	23.07
14	120	20	29.5		18.26	18.40		1.38	1.42		22.87	22.80
15	120	20	16		12.00	11.96		1.02	1.00		25.72	25.81

Mean	na	na	na		15.28	15.27		1.21	1.19		21.07	21.05

OBS = Observed, PRD = Predicted, L* is the luminance or lightness component, which ranges from 0 to 100, a* (from green to red), b* (from blue to yellow) are the two chromatic components, which range from -120 to +120, X_1 = Barrel temperature (°C), X_2 = Feed moisture content (g/100g), X_3 = Feed cowpea composition (g/100g), na = not applicable.

These results are in agreement with Bhattacharya *et al*. (1997), Prudencio-Ferreira and Area (1993) and Chakraborty *et al.* (2014) who reported significant decrease in L* of extruded millet-legume foods when legume content and temperature increased and attributed the changes to the amount of legumes, probably because of increased protein in the formulations resulting in a higher amino acid especially lysine in the melt and high working temperature which favour non-enzyme browning reaction. At reduced moisture level and high extrusion temperature, Noguchi *et al*., (1982), Prudencio-Ferreira and Area (1993) and Chaiyakul *et al*., (2009) are also of the opinion that there may be reduction in lysine content of extruded foods as a result of the formation of cross-linkage between lysine and other amino acids primarily due to heat induced reactions between the reducing sugars and amino groups of protein polypeptide chain in the legumes resulting in increased coloured product formation, thereby reducing extruded products L* as observed in this study.

Green to red chromatic (a*): The *a** chromatic value is redness on Hunter scale determines green, gray and red color of a product. Positive (+*a*) value refers to red, negative (-a) to green, and values near zero indicate gray (Pomeranz and Meloan, 1994). In this study, the value (a*) ranges between 0.48 and 2.46 with a mean value of 1.21 (Table 3), and the lowest value corresponding to formulation containing 16% cowpea flour, 28.4% moisture and extruded at 120°C temperature, while the highest was observed at 24% cowpea content, 15% moisture and 100°C temperature. The snacks tend to have green-to-red chromatic colour, indicating that all the different formulations have positive value. Increasing temperature from 100 to 120°C, moisture content (15-28.4%) and reducing feed cowpea composition (24-16%) tended to favour the transition of colour from green toward red. Probably, due to the formation of cross-linkage of amino acids produced from heat induced reactions and the reducing sugars and amino groups of protein polypeptide chain in the legumes resulting in increased coloured product formation. Similar observation was reported by Paes and Maga (2004) during the extrusion whole-grain flours of quality protein maize and normal maize.

Yellow to blue chromatic (b*): The yellowness colour quality characteristics (b*) as measured by the CIE standard in the rice-cowpea formulations varied from 16.00 to 25.72. Both the lowest and highest values were recorded in samples containing the same amount of cowpea (16%) and 20% moisture content but varied temperatures, 86.4 and 120°C respectively (Table 3). The significant ($p<0.05$) increase in b* value due to increased processing temperature may be possible due to low moisture level resulting in increased residence time, high shear and pressure associated with low moisture dough flow. High shear and pressure in the extruder barrel results in higher energy dissipation and high temperature generation, this has been found to increase the chances of Maillard reaction (Paes and Maga, 2004) and subsequent formation of yellow colour. It is clear from these results that HTST cooking significantly ($p<0.05$) have impacts on colour development in rice-cowpea formulations, hence the need to systematically optimize the process conditions for acceptable colour quality development.

Optimization of extrusion process

Fitting predictive models: Optimization of process conditions using RSM and CCD first require fitting experimental data to a specific model that defines the relationship between input variables (X_1, X_2, X_3) and the response variables. A quadratic polynomial model (Eqn. 7) was fitted to the experimental data (Table 3) to obtain a regression equation establishing the linear, square and interaction relationships between the independent and dependent variables. The coefficients of variables in the predictive model for response variables in coded forms are shown in Equations 8, 9 and 10 for L*, a*, and b* responses respectively. Analysis of variance (ANOVA) and regression analysis were conducted on the data from which the equations were derived to determine the coefficient of the regression models for the measured responses, in terms of linear, quadratic and interaction terms for the color characteristics and values were shown in Table 4.

$$L^* = 29.602 - 0.617X_1 + 1.080X_2 + 0.296X_3 + 0.003X^2_1 + 0.026X^2_2 + 0.027X^2_3 - 0.010\,X_1X_2 + 0.003X_1X_3 - 0.072\,X_2X_3\ (R^2 = 96.6) \qquad (8)$$

$$a^* = 1.304 - 0.048X_1 - 0.077X_2 + 0.445X_3 + 0.0003X^2_1 + 0.0005X^2_2 + 0.001X^2_3 + 0.001X_1X_2 - 0.002\,X_1X_3 - 0.001X_2X_3\ (R^2 = 98.4) \qquad (9)$$

$$b^* = -89.160 + 1.171X_1 + 2.761X_2 + 1.262X_3 - 0.005X^2_1 - 0.081X^2_2 - 0.016X^2_3 + 0.008\,X_1X_2 - 0.005\,X_1X_3 - 0.008\,X_2X_3\ (R^2 = 95.2) \qquad (10)$$

In Equations 8 – 10, the sign and magnitude of the coded variable coefficients indicate the effect of a variable on the response. Negative sign coefficient is an indication of decrease in dependent variable, but positive is an indication that the variable has synergistic effect. Significant interaction suggests that the level of one of the interaction variables can be increased while that of other decreased for constant value of the response (Adeyanju *et al*, 2016). The fitted models from this study therefore demonstrated that colour indices of extruded rice-cowpea flour blends are empirical function of the independent variables in their coded forms and can be established statistically to give satisfactory prediction of its application in natural form.

The results of ANOVA indicated significant ($p<0.05$) linear, quadratic and interaction effects of the process variables on snack lightness colour index (Table 4). This indicates that either individually or in combination, the independent variables have significant impact on L* (Eqn. 8). From Eqn. 8, X_1, X_1X_2 and X_2X_3 have significantly ($p<0.05$) negative effect as indicated by its ANOVA (Table 4).

Table 4: Results of ANOVA for the second order quadratic models of the colour responses

Model predictors	Regression coefficients (β)		
	L*	a*	b*
Model	29.602*	1.304	-89.160**
Linear effects			
X_1	-0.617**	-0.048**	1.171**
X_2	1.080**	-0.077	2.761**
X_3	0.296*	0.445**	1.262**
Quadratic effects			
$X_1 X_1$	0.003*	0.0003**	-0.005**
$X_2 X_2$	0.026*	0.0005	-0.081**
$X_3 X_3$	0.027**	0.001*	-0.016**
Interaction effects			
$X_1 X_2$	-0.010*	0.001**	0.008**
$X_1 X_3$	0.003*	-0.002**	-0.005**
$X_2 X_3$	-0.072*	-0.001**	-0.008
ANOVA			
R^2	0.9660	0.9840	0.9520
R^2_{adj}	0.9940	0.9760	0.9300
Lack-of-fit	ns	ns	ns

For the redness colour index (Eqn. 9), X_2 at both linear and quadratic levels have no significant ($p<0.05$) impact on its development. The yellow colour factor (Eqn. 10) was significantly ($p<0.05$) affected by all the extrusion conditions expect when there was an interaction between moisture content and feed cowpea level. This result is in agreement with earlier report by Danbaba *et al*, (2015) that extrusion cooking variables like moisture content, protein content of raw materials and high temperature plays important roles in determining quality characteristics of extruded starch based materials with added legumes. It can be deduced from these results therefore that the studied variables when combined as indicated in the models for colour indices could adequately define the system in practical applications.

Validation of fitted models: Trinh and Kang (2010) and Mason *et al.* (1986) stated that fitted regression model must shows a good fit before proceeding with investigation and optimization, if not the fitted response surface model is likely to lead to misleading results. Basically, two methods are used to validate fitted models, - graphical validation and numerical validation. The former involves the assessment of the model coefficients of determinations (R^2 and R^2_{adj}), Fishers *f*-value and the lack-of-fit tests, while the later involves examination of the residual graphs.

Based on the R^2 values of greater than 95% and 93% respectively for R^2 and R^2_{adj} (Table 4), the models could be said to appropriately and satisfactorily describe the relationships between the variables in practical application. R^2 measures how much of the observed variability in the experimental data could be accounted for by the model, while R^2_{adj} on the other hand modifies R^2 by taking into account the number of predictors variables in model, hence adding variable to the equation may not significantly change R^2, but significant change will be observed in R^2_{adj}. For any processes involving biological materials like in this study, Koocheki *et al*, (2009), Chauhan and Gupta (2004) and Danbaba *et al*, (2015) reported that R^2 between 75% and 80% are acceptable for fitting a satisfactory model, because at that levels, the R^2 better fit the experimental data even with variability in compositions of the materials. The R^2 therefore from this study indicated that only 3.40, 1.60 and 4.80% variation in L*, a* and b* respectively could not be explained by the Equations 8, 9 and 10 and hence its suitability for predicting the relationship and impact on response in practical applications. The significance ($p<0.05$) of replication error in comparison with model dependent error was determined as significant lack-of-fit. The results were non-significant ($p<0.05$) for all the colour parameters. In fitting predictive model, a non-significant lack-of-fit is desired as significant value may indicate the possibility of certain contributions in the regression response is not accounted for by the fitted model.

Residual as defined by the difference between the observed values obtained through experimentation and predicted or fitted values generated through fitting the values to the regression equations (Table 3) is presented graphically in Figures 2-4. From Figures 2 to 4, it is clear that there is a close relationship defined by the correlation coefficient (r^2) of 0.9961 (L*), 0.9783 (a*) and 0.9508 (b*). Trinh and Kang (2010) and Choudhury *et al.* (2011) reported that the plotted graph of observed versus predicted values of any response should form a straight line to justify adequacy of the model, and a departure from the straight line would indicate a departure from normal distribution of the residuals. It will be appropriate therefore to conclude that the fitted predictive models adequately approximates the color changes observed and can be used satisfactorily for the prediction of the values of the responses within the defined experimental range.

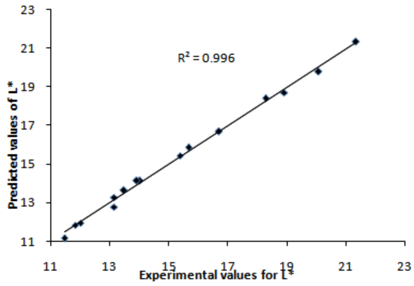

Figure 2: Correlation between experimental and predicted values for lightness

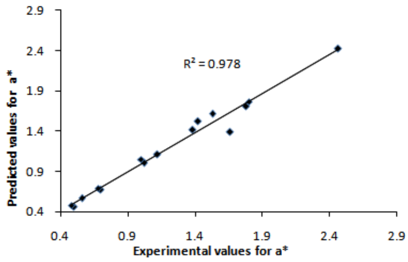

Figure 3: Correlation between experimental and predicted values for rediness

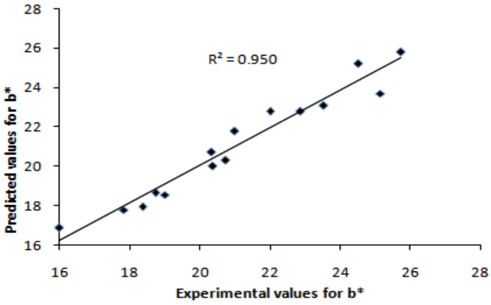

Figure 4: Correlation between experimental and predicted values for yellownes

Numerical optimization of process variables: Numerical optimization was carried out to develop extruded snack products which would have maximum color lightness (L*) and yellowness (b*) indices and minimum redness (a*) with acceptable sensory attributes. Numerical optimization was performed on the models developed to locate the optimal independent variables that will result in snacks with optimal color change. All the independent variables goals were set within the experimental design limits (Table 1) and importance of 3 were assigned to all. The goals for color indices were to maximize L* and b* and minimize a* (Table 5). Results indicated that the optimal process conditions were 120°C barrel temperature, 20.0 g water/100 g blend and 24.0 g cowpea/100 g rice flour. Under these conditions, the optimal responses predicted for color indices are 16.18 (L*), 2.06 (a*) and 22.16 (b*) with individual desirability of 0.9712 (L*), 0.9651 (a*) and 0.9773 (b*) and combined desirability function of 0.994. Desirability function of 0.994 for the simultaneous optimization which is close to 1 is an indication of the closeness of responses to its ideal value and therefore a measure of practicality of the models. The more closely the response approaches the ideal value, the closer the desirability is to 1. Solution with the highest desirability therefore is preferred.

Table 5: Goals, importance and optimum levels of process variables for rice-cowpea extruded snacks

Parameters	Goal	Lower limit	Upper limit	Importance	Optimum level
Independent variables					
Barrel temperature (°C)	In range	100	140	3	120
Feed moisture level (%)	In range	8	24	3	20
Cowpea composition (%)	In range	15	25	3	24
Response variables					
Lightness (L*)	Maximize	11.45	21.32	3	16.18
Redness (a*)	Minimize	0.48	2.46	3	2.06
Yellowness (b*)	Maximize	16.00	27.72	3	22.16

Consumer acceptability test: The mean sensory panellists rating for the extruded snacks are presented in Table 6. The results depicts that the addition of cowpea to rice flour and extrusion at high temperature impacted positively on consumer rating. The different samples even though differs significantly with respect to all the sensory parameters evaluated, all the samples are liked by the panel with mean score values of 8.56, 8.34, 8.44, 8.33, 8.67, 7.33 and 8.59 respectively for colour, aroma, taste, physical appearance, mouth feel, after taste and overall acceptability (Table 6). The snack produced at the optimal temperature (120^{o}C) containing the least cowpea composition (2.6 g/100 g rice flour) and extruded at 20% moisture content seems to be the highly rated formulation by the panellists scoring 9.88.

Table 6: Mean panellist ranking of rice-cowpea extruded snacks

Runs	Independent variables				Sensory properties ranking[1]						
	BRT	FMC	FBC		Colour	Aroma	Taste	Appearance	Mouth feel	After taste	Overall acceptability
1	100	15	8		8.89	7.77	9.13	6.89	8.87	6.78	8.88
2	140	15	8		9.56	8.76	9.11	7.12	8.67	6.89	8.67
3	100	25	8		8.11	8.45	8.16	7.56	8.13	6.89	8.34
4	140	25	8		8.32	8.99	8.56	8.66	9.11	8.76	7.67
5	100	15	24		9.08	9.43	8.09	8.71	9.07	6.77	7.65
6	140	15	24		9.00	9.12	8.33	8.34	8.75	6.88	8.11
7	100	25	24		8.67	8.11	8.34	8.71	8.56	7.77	7.89
8	140	25	24		8.44	8.21	7.99	9.00	8.57	7.66	8.89
9	86.4	20	16		8.34	7.66	9.22	7.89	8.76	7.89	9.66
10	153.6	20	16		9.13	7.20	8.32	8.56	8.67	7.61	9.12
11	120	11.6	16		8.12	8.11	8.11	8.56	9.11	6.89	8.95
12	120	28.4	16		8.11	8.11	8.45	9.06	6.89	7.08	7.89
13	120	20	2.6		8.23	8.52	7.89	9.11	8.79	7.09	9.88
14	120	20	29.5		8.12	8.45	7.99	8.67	9.08	7.03	8.56
15	120	20	16		8.23	8.23	8.98	8.11	9.05	7.99	8.66
Mean	NA	NA	NA		8.56	8.34	8.44	8.33	8.67	7.33	8.59

BRT=barrel temperature, FMC=feed moisture content, FBC=feed blend composition, CL=colour, ARM=aroma, TST=taste, APR= appearance, MF=mouth field. [1]Quality rating of 1 to 15 was used, where less than 6 is poor, 6-7 fair and greater than 8 is good.

Principal component analysis (PCA): PCA is a widely used multivariate analytical statistical technique that is often applied to QDA data to reduce the set of dependent variables (i.e., attributes) to a smaller set of underlying variables (called factors) based on patterns of correlation among the original variables (Lawless and Heymann, 1998; Chapman *et al*., 2001). The resulting data can therefore then be applied to profiling specific product characteristics, comparing and contrasting similar products based on attributes of important to consumers and also altering product characteristics with the goal of increasing market share for a given set of products (Chapman *et al*., 2001).

To appropriately highlight the factors and the contribution of each of the snacks attributes obtained from the different formulations based on the central composite design to the colour development and consumer acceptability, PCA was carried out using the colour indices and sensory attributes scores (Table 7). The results indicated that the first five principal components (PCs) contributed up to 94.9% of the total variation observed, with PC_1 contributing 30%, PC_2 responsible for 23.8%, PC_3 provides 17.3%, while PC_4 and PC_5 contributing 15.5 and 8.1% respectively. The main contributory parameter of PC_1 was the taste and physical appearance, while that of PC_2 was associated with aroma, PC_3 (mouth feel and after taste, PC_4 (mouth feel) and PC_5 (colour and surface appearance) (Table 7).

Table 7: Factor loadings of the first five principal components for sensory attributes

Sensory attributes	**PC_1**	**PC_2**	**PC_3**	**PC_4**	**PC_5**
Colour	0.358	0.468	-0.014	-0.087	0.789
Aroma	-0.260	0.617	0.205	-0.066	-0.352
Taste	0.586	-0.029	0.158	0.397	-0.161
Surface appearance	-0.607	-0.179	0.105	-0.058	0.424
Mouth feel	0.150	0.117	0.628	-0.613	-0.112
After taste	-0.047	-0.319	0.717	0.385	0.189
Overall acceptability	0.261	-0.503	-0.117	-0.551	0.014
Proportion of total variance (%)	30.00	23.80	17.30	15.50	8.10
Cumulative (%)	30.00	53.80	71.10	86.60	94.90

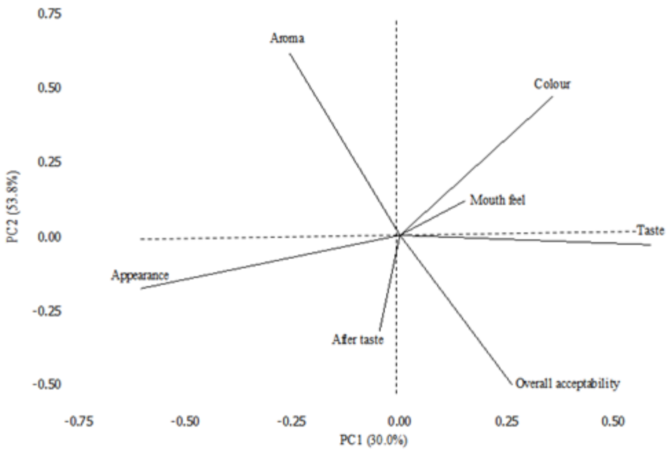

Fig. 5: Principal component analysis of the color and sensory attributes of extruded rice-cowpea extruded snacks

Based on the PCA graph (Fig. 5), the factors were grouped into four based on the correlation between the color characteristics and consumer acceptability ranking properties. As displayed in Fig. 5, the first group was on the positive side of PC_1 and PC_2 (color, mouth feel, taste and overall acceptability), while on the negative side are aroma, appearance and after taste.

IV. Conclusion

In this study, the statistical methodology, Response Surface Methodology and Central Composite Rotatable design and desirability function have been demonstrated to be effective and reliable in describing the relationship between barrel temperature, feed moisture and composition on the color indices and consumer acceptability of rice-cowpea extruded snacks. Second order mathematical models were developed by regression analysis of the experimental data obtained from 20 experimental runs. The results showed significant coefficients of the fitted models with non-significant lack-of-fit. Applying numerical optimization method and desirability function, optimization of the process variables indicated that the optimal process conditions were 120^{o}C barrel temperature, 20.0 g water/100 g blend and 24.0 g cowpea/100 g rice flour and response variables of 16.18 (L*), 2.06 (a*) and 22.16 (b*) with individual desirability of 0.9712 (L*), 0.9651 (a*) and 0.9773 (b*) respectively and combined desirability function of 0.994. Consumer preference analysis indicated that the snack produced at the optimal temperature (120^{o}C) containing the least cowpea composition (2.6 g/100 g rice flour) and extruded at 20% moisture content seems to be the highly rated formulation by the panellists scoring 9.88. While PCA analysis shows that first five principal components (PCs) contributed up to 94.9% of the total variation observed, with PC_1 contributing 30%, PC_2 responsible for 23.8%, PC_3 provides 17.3%, while PC_4 and PC_5 contributing 15.5 and 8.1% respectively. Finally, the reported research demonstrates the feasibility of RSM and CCRD model to optimize colour characteristics and consumer acceptability of rice-cowpea extruded snacks.

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