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Sensory evaluation of instant noodles produced from blends of sweet potato, soybean and corn flour

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Abstract

Wheat flour is unique for noodles production, but due to the high cost of wheat, its continuous use in a developing economy is no longer encouraged. This study was aimed at determining the sensory effect of full substitution of non-wheat flour in noodles production. D-optimal mixture-process experimental design of the response surface methodology (RSM) was adopted. Thirty-nine (39) samples of noodles were formulated, each with blends of sweet potato, soybean and corn flour. The respective formulation design constraints were sweet potato flour ($10\% \leq x_1 \leq 61\%$), soybean flour ($5\% \leq x_2 \leq 20\%$), corn flour ($5\% \leq x_3 \leq 30\%$), and water ($25\% \leq x_4 \leq 37\%$). Other components of the formulation were salt (2.5%), sodium carbonate (0.5%), guar gum (0.5%), and soy lecithin (0.5%). The processing factors investigated were mixing time (2 mins $\leq z_1 \leq$ 10 mins), frying time (1 min $\leq z_2 \leq$ 3 min), and frying temperature (140°C $\leq z_3 \leq$ 160°C). The formulated instant noodles were subjected to a 9-point hedonic scale sensory evaluation by a panel of semi-trained panellists who had been eating noodles for a long time, and the best formulations were determined in accordance with a preference test. Optimization analysis on the data obtained from the sensory session showed that blend of 23.31% of sweet potato flour, 28.53% of soya bean flour, 18.02% of corn flour, 26.15% water, 2.75 minutes mixing time, 1.35minutes frying time, and 140°C frying temperature, with the highest desirability index of 0.72, produced the best composite instant noodles in terms of taste, texture, flavour, appearance, and overall acceptability. The proximate compositions, cooking, physical and sensory properties of this optimal formulation were: 13.17% moisture content, 6.62% ash content, 22.86 crude protein, and 37.71% energy value, 16.00% crude fat and, 4.64% crude fibre, 5.42 minutes cooking time, 26.45 g cooking weight, 164.49 water absorption index, 0.77 bulk density, 6.41 taste, 8.25 texture, 7.66 flavour, 6.22 appearance, and 5.33 overall acceptability. The D-optimal mixture-process design was used to evaluate the effect of changes in mixture compositions and the three processing factors on the main proximate, cooking and physical qualities of instant noodles. The effects were established through analysis of variance at 5% level of significance. The quadratic x mean model for taste, the reduced special cubic x cubic model for texture, the reduced special cubic x cubic model flavour, the quadratic x mean model for appearance, and the quadratic x mean model for overall acceptability were all found to be statistically significant at 5% level of significance ($p<0.05$).

1. Introduction

In Nigeria, ready-to-eat baked products (snacks) consumption is continually growing and there has been increasing reliance on imported wheat (Olaoye *et al.,* 2006). Since wheat cannot perform well under tropical climate, the country had over the years been dependent on wheat imports mostly from the United States. Wheat importation had detrimental effects on the Nigerian economy involving huge expenditure of foreign exchange. The economy of the country would be improved if other staple food crops that are grown locally are exploited. In Nigeria, staple crops that are grown which can be used as substitutes for wheat for baked foods include cassava, yam or sweet potatoes and cereals (Shittu *et al.,* 2007; Baljeet *et al.,* 2014; Oluwamukomi *et al.,* 2011).

Efforts have been made to partially replace wheat flour with non-wheat flours as a possibility for increasing

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the utilization of crops. The extrusion process for the production of expanded product from green gram and rice was studied by Chakraborty and Banerjee (2009). Study of the impact of ingredient formulation and processing parameters on colour and texture of instant noodles was carried out by Widjaya (2010). Mensah (2011) modified noodles formulation using bambara groundnuts starch, composited with defatted bambara groundnut flour. The optimisation of wheatgrass fortified steamed rice cake, using response surface methodology, was reported by Das *et al.* (2014). Optimization of pasta supplemented with millet was reported by Gull *et al.* (2015). Optimization of fenugreek enriched extruded product using response surface methodology was carried out by Wani and Kumar (2016). Partially replacement of wheat flour with non-wheat flours in the production of other baked products have also been researched on (Hudson and Ogunsua, 1976; Nout, 1977; Ayo and Gaffa, 2002; Sanni *et al.,* 2007; Shittu *et al.,* 2009; Orunkoyi, 2009). The are other staple food crops that are grown locally which can be used as substitutes for wheat that are yet to be exploited.

The objective of this study was to optimize the formulation and some process parameters of noodles production from composite blends of sweet potatoes, maize and soybean flour, employing a D-optimal mixture -process design methodology.

2. Materials and methods

2.1 Materials

Soybean, yellow corn, sweet potato and salt were purchased from the local market at Mile 12 in Lagos, Nigeria. Other ingredients were obtained from a food chemical market in Lagos. The chemicals used were of analytical grade. The equipment and apparatus used in the study include Master chef deep fryer (PRODUCT CODE: 3854942 BRAND: Master Chef), manual kneader (Royalty line hand mixer - 200W Royalty Line RL-HM250T.3 MSY), steaming machine (Binatone Rice Cooker - RCSG 2804), and noodles maker (Stainless steel fresh OxGord Pasta Maker Machine).

2.2 Preparation of soybean flour

Soybean flour was produced according to the methods of Oluwamukomi *et al.* (2011). Soybeans were cleaned, sorted, washed and boiled in water at 100°C for 30 mins. It was dehulled manually, oven dried at 70°C for 15 hrs and milled in a disc attrition mill to obtain the flour followed by sieving using a muslin cloth. The resultant fine flour was stored in air tight polyethylene bags at room temperature for further use.

2.3 Preparation of sweet potato flour

Sweet potato flour was produced according to the methods of Julianti *et al.* (2017). Sweet potato tubers were washed, peeled and cut into thin slices, spread in a tray and was oven dried at 60°C for 10 hrs after which it was milled into flour. The flours were screened through an 80-mesh sieve, and then packed in sealed polyethylene bags and stored at room temperature until they are required for use.

2.4 Preparation of corn flour

The corn flour was prepared using the traditional method. Traditionally, corn cobs are generally dried such that the grains are at safe moisture content. The cobs were dehusked, the grains shelled, dried further, cleaned thoroughly and milled. The milled sample was sieved to obtain a fine sample of corn flour.

2.5 Experimental design

Design-Expert software (version 11, Stat-Ease Inc., USA) was used for experimental design and statistical evaluation of the data. A constrained D-optimal mixture-process experimental design, totaling 39 randomized experimental runs, was employed. The D-optimal mixture-process design was used to evaluate the effect of changes in mixture compositions and the three processing factors on dependent variables and statistical optimization of the formulation. Both process and mixture optimizations are possible by this method. Four major variable components, four constant components, with three processing factors were investigated. The dependent variables (responses) were selected as representing the main proximate, cooking and physical qualities of instant noodles. A semi-trained panel consisting of ten men was constituted to evaluate the noodles using a 9-point hedonic scale ranging from 1 (extremely disliked) to 9 (extremely liked). The panelists were asked to score for texture, taste, appearance, flavour and overall acceptability. The design matrix for the D-Optimal mixture – process design is presented in Table 1.

3. Results

The mean sensory scores, based on the nine-point hedonic scale, for the thirty-nine, formulated instant noodle samples from composite blends of sweet potato, corn and soybean flours are presented in Table 2.

3.1 Statistical analysis of experimental results

Appropriate Scheffe canonical models were fitted to the mean sensory scores data for each mean sensory response (texture, taste, appearance, flavour, and overall

Table 1. D-Optimal mixture–process design matrix

Run	x_1 (%)	x_2 (%)	x_3 (%)	x_4 (%)	z_1 (mins)	z_2 (mins)	z_3 (°c)	c_1 (%)	c_2 (%)	c_3 (%)	c_4 (%)
1	46	20	5	25	10	3	140	2.5	0.5	0.5	0.5
2	21	20	30	25	10	1	160	2.5	0.5	0.5	0.5
3	22	20	17	37	10	1	160	2.5	0.5	0.5	0.5
4	49	5	5	37	10	1	140	2.5	0.5	0.5	0.5
5	36.5	5	17.5	37	2	1	140	2.5	0.5	0.5	0.5
6	41.5	12.5	5	37	2	3	160	2.5	0.5	0.5	0.5
7	33.5	20	17.5	37	2	1	160	2.5	0.5	0.5	0.5
8	10	19	30	37	2	2	150	2.5	0.5	0.5	0.5
9	21	20	30	25	10	3	140	2.5	0.5	0.5	0.5
10	42.7	15	13.3	25	6	2	150	2.5	0.5	0.5	0.5
11	61	5	5	25	2	1	160	2.5	0.5	0.5	0.5
12	36	5	30	25	10	3	140	2.5	0.5	0.5	0.5
13	49	5	5	37	10	1	140	2.5	0.5	0.5	0.5
14	21	20	30	25	2	1	160	2.5	0.5	0.5	0.5
15	61	5	5	25	10	3	140	2.5	0.5	0.5	0.5
16	28.5	12.5	30	25	2	3	160	2.5	0.5	0.5	0.5
17	55	5	5	31	2	3	140	2.5	0.5	0.5	0.5
18	15.5	20	30	30.5	2	3	160	2.5	0.5	0.5	0.5
19	46	20	5	25	2	3	140	2.5	0.5	0.5	0.5
20	53.5	12.5	5	25	2	1	140	2.5	0.5	0.5	0.5
21	21	30	30	25	2	3	140	2.5	0.5	0.5	0.5
22	46	20	5	25	10	1	140	2.5	0.5	0.5	0.5
23	25.4	13.8	19.8	37	10	3	140	2.5	0.5	0.5	0.5
24	10	19	30	37	10	3	160	2.5	0.5	0.5	0.5
25	10	19	30	37	6	3	150	2.5	0.5	0.5	0.5
26	23.3	9.7	30	33	2	1	140	2.5	0.5	0.5	0.5
27	48.5	5	17.5	25	2	1	140	2.5	0.5	0.5	0.5
28	24	5	30	37	10	3	160	2.5	0.5	0.5	0.5
29	34	20	5	37	2	1	140	2.5	0.5	0.5	0.5
30	34	20	5	37	10	3	160	2.5	0.5	0.5	0.5
31	22	20	17	37	2	3	140	2.5	0.5	0.5	0.5
32	21	20	30	25	2	1	140	2.5	0.5	0.5	0.5
33	36	5	30	25	2	3	140	2.5	0.5	0.5	0.5
34	10	19	30	37	2	1	140	2.5	0.5	0.5	0.5
35	21	20	30	25	10	1	140	2.5	0.5	0.5	0.5
36	10	19	30	37	6	1	150	2.5	0.5	0.5	0.5
37	10	19	30	37	10	2	150	2.5	0.5	0.5	0.5
38	33.5	20	17.5	25	2	2	160	2.5	0.5	0.5	0.5
39	42.5	5	17.5	31	10	3	160	2.5	0.5	0.5	0.5

x_1= sweet potato flour; x_2= corn flour; x_3= soy bean flour; x_4= water; c_1= salt; c_2= sodium carbonate; c_3= guar gum; c_4= soy lecithin; z_1= mixing time; z_2= frying time; z_3= frying temperature.

acceptability). All the missing terms in the models were aliased. The statistical significance of the terms in the Scheffe canonical regression models was examined by ANOVA for each response, and the adequacy of the models was evaluated by coefficient of determination. r^2, F-value, and model p-value at the 0.05 level of significance. The models were subjected to lack-of-fit and adequacy tests and only the model parameters that were found to be statistically significant were retained in the final fitted Scheffe canonical models. The fitted models for all the attributes were used to generate three-dimensional response surfaces as well as their contour plots using the DESIGN EXPERT 11.0 statistical software.

The summary of the model regression coefficients in terms of coded factors for the sensory responses (texture, taste, appearance, flavour, and overall acceptability) are presented in Tables 3 to 7. The summary of the analysis of variance (ANOVA) for the responses is presented in Tables 8 and 9.

The final fitted Scheffe canonical models for the sensory responses (texture, taste, appearance, flavour, and overall acceptability) are presented as Equations 1-5. The ten 3-D surface mix-process plots and their contour mix-process plots for the sensory responses are presented in Figures 1 to 5.

Taste Model:

$$y_{taste} = 7.16951x_1 + 5.89824x_2 + 9.21853x_3 - 17.3493x_4 - 6.24466x_{12} - 3.94872x_{13} + 9.23689x_{14} - 4.93225x_{23} + 0.024317x_{24} + 56.3858x_{34} \quad (1)$$

Texture Model:

$$y_{texture} = 7.02346x_1 + 24.1123x_2 + 13.4045x_3 - 48.999x_4 - 35.9195x_{12} - 14.0816x_{13} + 58.2605x_{14} - 0.73912x_1z_1 + 0.748581x_1z_2 + 0.060819x_1z_3 - 59.9743x_{23} - 25.1284x_{24} + 3.64647x_2z_1 - 2.47439x_2z_2 - 6.84451x_2z_3 + 77.2376x_{34} - 2.41795x_3z_1 + 0.643297x_3z_2 + 1.43859x_3z_3 + 4.68261x_4z_1 - 3.31731x_4z_2 + 6.52836x_4z_3 + 102.507x_{123} + 73.2715x_{124} + 7.97434x_{134} + 240.121x_{234} + 35.2783x_{123}z_1z_2 - 13.9188x_{123}z_1z_3 + 15.7502x_{123}z_2z_3 - 0.80361x_{12}z_1z_2z_3 - 4.40357x_{13}z_1z_2z_3 - 3.86426x_{23}z_1z_2z_3 + 58.6539x_{123}z_1z_2z_3 \quad (2)$$

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Flavour Model:

$$y_{flavour} = 6.48867x_1 - 0.0141693x_2 + 13.9884x_3 - 38.6938x_4 - 2.60169x_{12} - 12.0013x_{13} + 44.3917x_{14} + 0.12267x_1z_1 - 0.59059x_1z_2 + 0.243758x_1z_3 - 22.5319x_{23} + 17.6134x_{24} + 2.12578x_2z_1 - 1.13364x_2z_2 - 4.83436x_2z_3 + 40.2138x_{34} - 1.41338x_3z_1 + 0.936572x_3z_2 + 0.203473x_3z_3 + 3.33129x_4z_1 - 4.85815x_4z_2 + 6.8899x_4z_3 + 70.0804x_{123} + 41.3743x_{124} + 62.6767x_{134} + 215.499x_{234} + 22.0638x_{123}z_1z_2 - 16.6402x_{123}z_1z_3 + 17.8549x_{123}z_2z_3 - 0.541558x_{12}z_1z_2z_3 - 2.73658x_{13}z_1z_2z_3 - 3.24329x_{23}z_1z_2z_3 + 45.2462x_{123}z_1z_2z_3 \quad (3)$$

Appearance Model:

$$y_{appearance} = 6.77129x_1 + 9.86222x_2 + 5.07002x_3 + 51.4756x_4 - 10.9585x_{12} + 1.50439x_{13} - 73.2924x_{14} + 2.79549x_{23} - 110.885x_{24} - 26.175x_{34} \quad (4)$$

Overall Acceptability Model:

$$y_{acceptability} = 6.8763 - 1.94925 + 12.4167 + 25.2166 + 3.93907 - 10.169 - 49.2342 - 6.37425 - 35.9175 - 4.92447 \quad (5)$$

4. Discussion

The Model F-value of 6.75 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant. The Lack of Fit F-value of 0.46 implies the Lack of Fit is not significant relative to the pure error. There is a 84.66% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good, we want the model to fit. The Predicted R^2 of 0.4313 is in reasonable agreement with the Adjusted R^2 of 0.5765; i.e. the difference is less than 0.2. The adequacy precision value 10.4325 indicates an adequate signal.

The texture model F-value of 12.40 and p-value of 0,0023 implies that both the model and the model main linear terms are significant. There is only a 0.23% chance that an F-value this large could occur due to noise. The Lack of Fit F-value of 1.06 implies the Lack of Fit is not significant relative to the pure error. There is a 62.48% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good, we want the model to fit. The negative Predicted R^2 implies that the overall mean may be a better predictor of texture than the current model. A higher order model may also predict better. Adeq Precision of 13.133 indicates an adequate signal.

The flavour model F-value of 4.87 and p-value of 0.0274 implies that both the model and the model main linear terms are significant. There is only a 2.74% chance that an F-value this large could occur due to noise. The Lack of Fit F-value of 2.45 implies the Lack of Fit is not significant relative to the pure error. There is a 44.90% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good, we want the model to fit. A negative Predicted R^2 implies that the overall mean may be a better predictor of flavour than the current model. A higher order model may also predict better. Adeq Precision of 8.219 indicates an adequate signal. This model can be used to navigate the design space.

The appearance model F-value of 5.35 and p-value of 0,0003 implies that both the model and the model main linear terms are significant. There is only a 0.03% chance that an F-value this large could occur due to noise. The Lack of Fit F-value of 0.26 implies the Lack of Fit is not significant relative to the pure error. There is a 93.84% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good, we want the model to fit. The Predicted R^2 of 0.3195 is in reasonable agreement with the Adjusted R^2 of 0.5074; i.e. the difference is less than 0.2. Adeq Precision of 10.406 indicates an adequate signal. This model can be used to navigate the design space.

The overall acceptability model F-value of 4.65 and p-value of 0,0007 implies that both the model and the model main linear terms are significant. There is only a 0.07% chance that an F-value this large could occur due to noise. The Lack of Fit F-value of 0.39 implies the Lack of Fit is not significant relative to the pure error. There is a 88.09% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good, we want the model to fit. The Predicted R^2 of 0.2878 is in reasonable agreement with the Adjusted R^2 of 0.4640; i.e. the difference is less than 0.2. Adeq Precision of 8.293 indicates an adequate signal. This model can be used to navigate the design space.

The quadratic x mean taste model, the reduced special cubic x cubic texture model, the reduced special cubic x cubic flavour model, the quadratic x mean appearance model, and the quadratic x mean overall acceptability model, were all found to be statistically significant at 5% level of significance ($p<0.05$). The analysis of variances (ANOVA) also showed that all the model terms were statistically significant.

5. Conclusion

Instant noodles from composite blends of sweet potato, corn, soybean flours, and water were prepared and optimized using D-optimal mixture-process experimental design.

Blends of flours from these locally available crops which are produced in large quantities are considered advantageous in developing countries as it reduces the importation of wheat flour and encourages the use of locally grown crops as flour. This research work was carried out in order to evaluate the sensory attributes of formulated instant noodles from the composite blends. Five sensory attributes (texture, taste, appearance, flavour, and overall acceptability) were evaluated. The fitted models for all the attributes were used to generate three-dimensional response surfaces as well as contour plots. The design of the experiments and the analysis of

Table 2. Mean of sensory scores for the formulated composite instant noodles

Run	Texture	Taste	Appearance	Flavour	Overall acceptability
1	7	6	6	5	6
2	2	3	4	2	1
3	7	7	7	7	7
4	3	2	3	4	1
5	4	5	6	5	4
6	1	1	1	1	1
7	7	7	6	6	5
8	8	7	7	6	6
9	7	7	6	7	6
10	5	5	7	5	5
11	7	6	7	7	7
12	6	7	6	7	6
13	4	5	7	5	5
14	7	7	7	6	6
15	7	8	7	6	7
16	7	7	6	7	6
17	6	5	3	3	2
18	6	5	5	6	4
19	6	5	4	4	4
20	6	6	5	6	6
21	6	6	6	6	6
22	7	7	7	7	7
23	6	6	5	5	5
24	8	8	8	8	8
25	8	8	6	6	7
26	9	9	9	9	9
27	7	7	7	7	7
28	9	8	8	8	8
29	1	1	1	1	1
30	1	1	1	1	1
31	2	2	2	2	2
32	8	8	9	7	7
33	7	7	6	7	7
34	9	9	9	9	9
35	8	8	9	8	8
36	9	8	8	7	8
37	9	8	7	8	8
38	3	3	5	3	1
39	7	8	6	7	7

Table 3. Taste model regression coefficients in terms of coded factors

Model Terms	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
x_1	7.17	1	0.8374	5.46	8.88	3.34
x_2	5.9	1	23.4	-41.95	53.75	498.23
x_3	9.22	1	5.48	-1.99	20.42	66.97
x_4	-17.35	1	46.63	-112.72	78.03	950.51
x_{12}	-6.24	1	32.67	-73.07	60.58	140
x_{13}	-3.95	1	9.66	-23.71	15.82	16.59
x_{14}	9.24	1	60.36	-114.21	132.68	266.41
x_{23}	-4.93	1	36.33	-79.23	69.36	172.99
x_{24}	0.0243	1	71.58	-146.38	146.43	113.78
x_{34}	6.39	1	61.11	-68.6	181.37	200.71

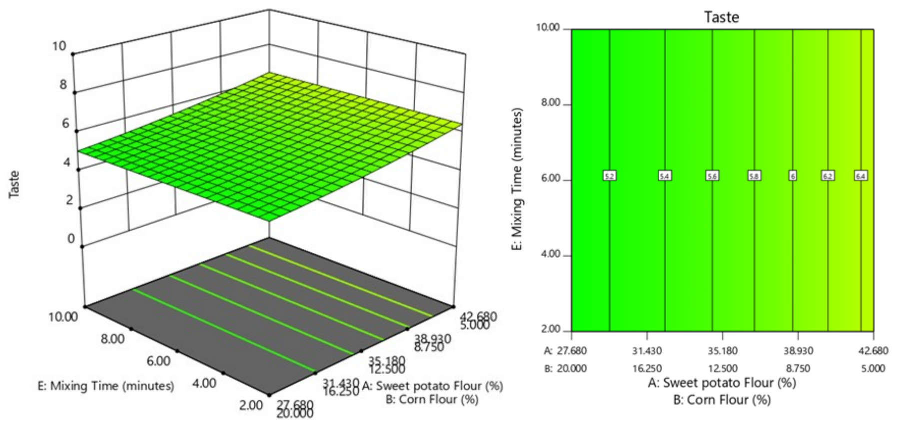

Figure 1. The 3-D Surface mix-process graphs and their contour mix-process for taste

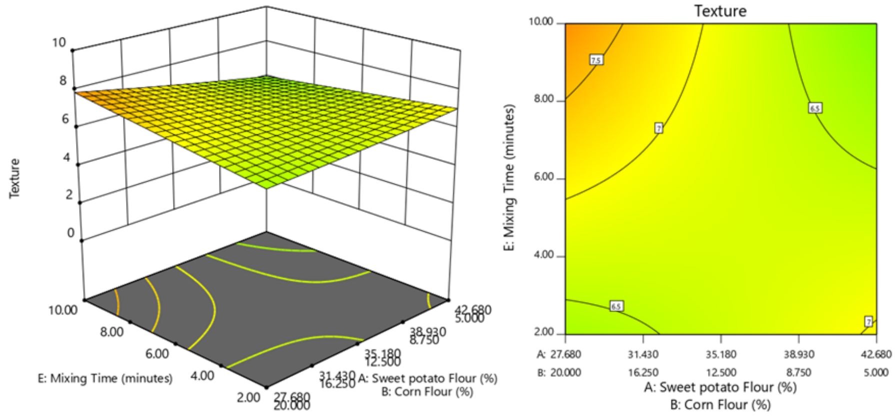

Figure 2. The 3-D Surface mix-process graphs and their contour mix-process for texture

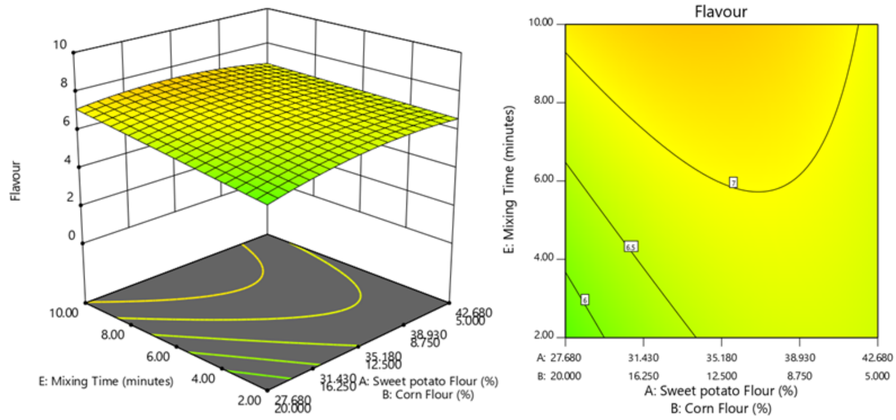

Figure 3. The 3-D Surface mix-process graphs and their contour mix-process for flavour

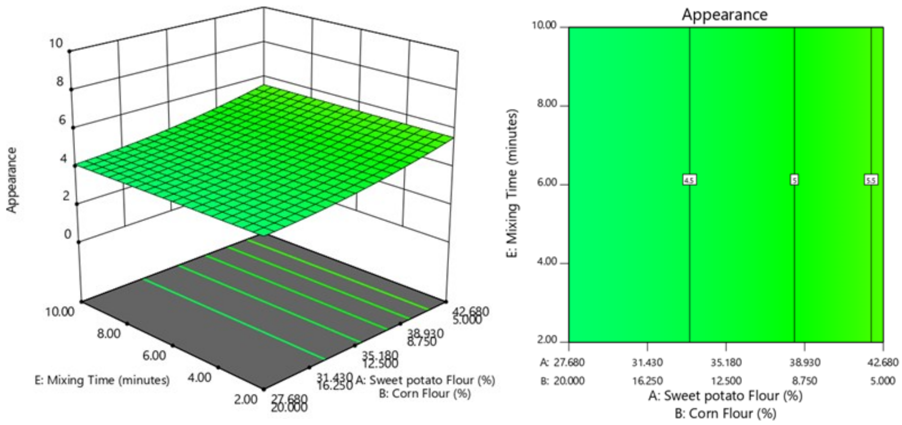

Figure 4. The 3-D Surface mix-process graphs and their contour mix-process for appearance

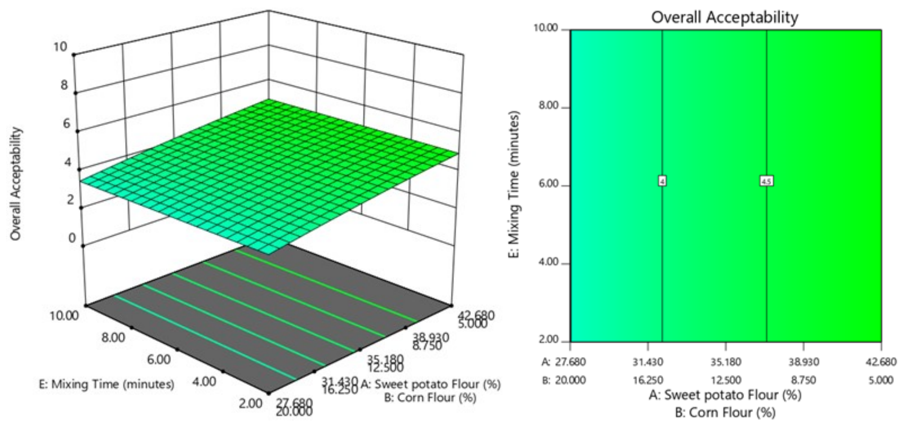

Figure 5. The 3-D Surface mix-process graphs and their contour mix-process for overall acceptability

Table 4. Texture model regression coefficients in terms of coded factors

Model Terms	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
x_1	7.02	1	0.5087	5.78	8.27	5.12
x_2	24.11	1	18.94	-22.22	70.44	1354.83
x_3	13.40	1	5.62	-0.3413	27.15	292.28
x_4	-49.00	1	30.30	-123.15	25.15	1666.35
x_{12}	-35.92	1	26.83	-101.58	29.74	392.08
x_{13}	-14.08	1	10.06	-38.7	10.54	74.68
x_{14}	-58.26	1	39.46	-38.3	154.82	472.82
x_1z_1	-0.7391	1	0.3555	-1.61	0.1308	2.40
x_1z_2	0.7486	1	0.4022	-0.2355	1.73	3.08
x_1z_3	0.0608	1	0.4127	-0.9491	1.07	3.24
x_{23}	-59.97	1	38.6	-154.41	34.47	810.78
x_{24}	-25.13	1	108.7	-291.1	240.84	1089.16
x_2z_1	3.65	1	1.06	1.04	6.25	3.87
x_2z_2	-2.47	1	1.41	-5.92	0.9671	6.76
x_2z_3	-6.84	1	1.59	-10.73	-2.96	7.88
x_{34}	77.24	1	51.46	-48.68	203.15	590.84
x_3z_1	-2.42	1	0.6917	-4.11	-0.7253	3.97
x_3z_2	0.6433	1	0.8401	-1.41	2.7	5.85
x_3z_3	1.44	1	0.9279	-0.8319	3.71	6.35
x_4z_1	4.68	1	1.37	1.32	8.042	3.02
x_4z_2	-3.32	1	1.41	-6.774	0.1395	3.20
x_4z_3	6.53	1	1.78	2.16	10.89	4.43
x_{123}	102.51	1	45.86	-9.70	214.72	41.19

Table 5. Flavour model regression coefficients in terms of coded factors

Model Terms	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
x_1	6.49	1	0.7389	4.68	8.3	5.12
x_2	-0.0142	1	27.5	-67.31	67.28	1354.83
x_3	13.99	1	8.16	-5.98	33.95	292.28
x_4	-38.69	1	44.01	-146.39	69	1666.35
x_{12}	-2.6	1	38.97	-97.97	92.77	392.08
x_{13}	-12	1	14.61	-47.76	23.76	74.68
x_{14}	44.39	1	57.32	-95.86	184.64	472.82
x_1z_1	0.1227	1	0.5163	-1.14	1.39	2.4
x_1z_2	-0.5906	1	0.5841	-2.02	0.8387	3.08
x_1z_3	0.2438	1	0.5995	-1.22	1.71	3.24
x_{23}	-22.53	1	56.06	-159.7	114.63	810.78
x_{24}	17.61	1	157.87	-368.69	403.92	1089.16
x_2z_1	2.13	1	1.55	-1.66	5.91	3.87
x_2z_2	-1.13	1	2.04	-6.13	3.86	6.76
x_2z_3	-4.83	1	2.31	-10.47	0.8062	7.88
x_{34}	40.21	1	74.74	-142.67	223.09	590.84
x_3z_1	-1.41	1	1	-3.87	1.04	3.97
x_3z_2	0.9366	1	1.22	-2.05	3.92	5.85
x_3z_3	0.2035	1	1.35	-3.09	3.5	6.35
x_4z_1	3.33	1	1.99	-1.55	8.21	3.02
x_4z_2	-4.86	1	2.05	-9.88	0.1625	3.2
x_4z_3	6.88	1	2.59	0.5514	13.23	4.43
x_{123}	70.08	1	66.6	-92.89	233.05	41.19
x_{124}	41.37	1	231.02	-523.92	606.67	158.77
x_{134}	62.68	1	74.67	-120.04	245.4	17.37
x_{234}	215.5	1	241.4	-375.19	806.19	368.18
$x_{123}z_1z_2$	22.06	1	11.7	-6.73	50.86	1.23
$x_{123}z_1z_3$	-16.64	1	11.91	-45.78	12.5	1.26
$x_{123}z_2z_3$	17.85	1	13.12	-14.26	49.97	1.53
$x_{12}z_1z_2z_3$	0.5416	1	2.78	-6.26	7.34	1.88
$x_{13}z_1z_2z_3$	-2.74	1	3.19	-10.54	5.07	3.46
$x_{23}z_1z_2z_3$	-3.24	1	6.08	-18.13	11.64	7.09
$x_{123}z_1z_2z_3$	45.25	1	32.72	-34.82	125.31	9.53

Table 6. Appearance model regression coefficients in terms of coded factors

Model Terms	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
x_1	6.77	1	0.8638	5	8.54	3.34
x_2	9.86	1	24.13	-39.5	59.22	498.23
x_3	5.07	1	5.65	-6.49	16.63	66.97
x_4	51.48	1	48.1	-46.91	149.86	950.51
x_{12}	-10.96	1	33.7	-79.89	57.97	140
x_{13}	1.5	1	9.97	-18.88	21.889	16.59
x_{14}	-73.29	1	62.26	-200.63	54.05	266.41
x_{23}	2.8	1	37.47	-73.84	79.43	172.99
x_{24}	-110.88	1	73.84	-261.91	40.14	113.78
x_{34}	-26.18	1	63.04	-155.1	102.75	200.71

Table 7. Overall acceptability model regression coefficients in terms of coded factors

Model Terms	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
x_1	6.88	1	1.03	4.78	8.98	3.34
x_2	-1.95	1	28.68	-60.6	56.71	498.23
x_3	12.42	1	6.72	-1.32	26.15	66.97
x_4	25.22	1	57.16	-91.69	142.12	950.51
x_{12}	3.94	1	40.05	-77.97	85.85	140
x_{13}	-10.17	1	11.85	-34.4	14.06	16.59
x_{14}	-49.23	1	73.98	-200.55	102.08	266.41
x_{23}	-6.37	1	44.53	-97.44	84.69	172.992
x_{24}	-35.92	1	87.74	-215.38	143.54	113.78
x_{34}	-4.92	1	74.91	-158.13	148.28	200.71

Table 8. Summary of the analysis of variance for the responses

Response	Source	Sum of Squares	df	Mean Square	F value	Prob>F
	Model	131.96	9	14.66	6.75	**<0.0001**
	Linear Mixture	75.16	3	25.05	11.53	**<0.0001**
	Residual	63.01	29			
	Lack of Fit	58.51	28	2.17	0.4644	0.8466*
Taste (Y_{taste})	Pure Error	4.5	1	2.09		
	Cor Total	194.97	38	4.5		
	Std. Dev.	1.47		R^2	0.6768	
	Mean	5.97		Adjusted R^2	0.5765	
	C.V. %	24.67		Predicted R^2	0.4313	
				Adeq. Precision	10.4325	
	Model	207.63	32	6.49	12.4	**0.0023**
	Linear Mixture	66.24	3	22.08	42.19	0.0002
	Residual	3.14	6	0.5234		
	Lack of Fit	2.64	5	0.528	1.06	0.6248*
Texture ($Y_{texture}$)	Pure Error	0.5	1	0.5		
	Cor Total	210.77	38			
	Std. Dev.	0.7234		R^2	0.9851	
	Mean	6.08		Adjusted R^2	0.9056	
	C.V. %	11.9		Predicted R^2	-5.366	
				Adeq. Precision	13.1327	
	Model	172.04	32	5.38	4.87	**0.0274**
	Linear Mixture	72.82	3	24.27	21.98	0.0012
	Residual	6.62	6	1.1		
	Lack of Fit	6.12	5	1.22	2.45	0.4490*
Flavour ($Y_{flavour}$)	Pure Error	0.5	1	0.5		
	Cor Total	178.67	38			
	Std. Dev.	1.05		R^2	0.9629	
	Mean	5.67		Adjusted R^2	0.7652	
	C.V. %	18.54		Predicted R^2	-5.9869	
				Adeq. Precision	8.2192	

Figures in **bold** under the Prob>F column indicates significant difference

Table 9. Summary of the analysis of variance for the responses (Continue)

Response	Source	Sum of Squares	df	Mean Square	F value	Prob>F
Appearance ($Y_{appearance}$)	Model	111.31	9	12.37	5.35	**0.0003**
	Linear Mixture	62.59	3	20.86	9.02	**0.0002**
	Residual	67.05	29	2.31		
	Lack of Fit	59.05	28	2.11	0.2636	0.9384*
	Pure Error	8	1	8		
	Cor Total	178.36	38			
	Std. Dev.	1.52		R^2	0.6768	
	Mean	5.87		Adjusted R^2	0.5765	
	C.V. %	25.9		Predicted R^2	0.4313	
				Adeq. Precision	10.4325	
Overall acceptability ($Y_{overall\ acceptability}$)	Model	136.76	9	15.2	4.65	**0.0007**
	Linear Mixture	65.35	3	21.78	6.67	0.0015
	Residual	94.68	29	3.26		
	Lack of Fit	86.68	28	3.1	0.387	0.8809
	Pure Error	8	1	8		
	Cor Total	231.44	38			
	Std. Dev.	1.81		R^2	0.5909	
	Mean	5.41		Adjusted R^2	0.464	
	C.V. %	33.4		Predicted R^2	0.2878	
				Adeq. Precision	8.2926	

Figures in **bold** under the Prob>F column indicates significant difference

the experimental results were done by using the D-optimal statistical method. The optimal composition of the instant noodles' formulation was obtained based on the desirability criterion of each response. From the numerical optimization through the desirability function, the formulation that produced instant noodles of highest desirability index of 0.723 are: 23.305% of sweet potato flour, 28.529% of soya bean flour, 18.021% of corn flour, 26.145% water, 2.749 mins mixing time, 1.35 mins frying time, and 140°C frying temperature, The proximate composition of this optimal formulation are: 13.17% moisture content, 6.616% ash content, 22.862 crude protein, and 37.707% energy value, 16.001% crude fat and, 4.643% crude fibre. These results are comparable with the nutritional profile of the different noodle brands available locally. The quantitative effect of the mixture compositions and the three processing parameters on the main proximate qualities of instant noodles could be predicted. The effects were established through analysis of variance at 5% level of significance.

The study has shown that composite blends of sweet potato, corn, and soybean flours, has the potential to produce noodles of acceptable quality. The research has shown that the nutritional and sensory quality of the instant noodles from composite flour blends depends on the appropriate quantization of the ingredients and proper production settings. The research has also been able to achieve good quality noodles with good overall acceptability through the use of appropriate experimental design techniques (Mixture-process design). Mixture-process design methodology is a powerful tool in product development.

Storability studies should be carried out to determine the shelf life of composite blends instant noodles using suitable packaging material. The physicochemical properties of the composite blends instant noodles should also, be determined.

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