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Neural network modeling and optimization of process parameters for production of *chhana* cake using genetic algorithm

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Abstract

Chhana cake, locally termed *chhana podo*, is a baked traditional dairy product of India. The present study was undertaken for optimization of process parameters pertaining to production of *chhana podo*. Independent variables, namely, moisture content of feed-mix: 52.5 - 62.5% (wb), baking temperature: 60 - 180°C, baking time: 1 - 9 h and height of feed-mix: 1 - 5 cm were selected heuristically and their effect on dependent variables, namely, hardness, whiteness index, yellowness index, tint of crust and crumb, moisture content and expansion ratio of chhana podo were studied. Although quadratic models fitted to responses exhibited relative deviation percent (Rd) ranging from 1.214 to 5.406%; lack of fit was significant for all responses except crust yellowness index and crust tint. Neural network modeling was adopted (Rd for training = 1.739%, Rd for validation = 1.845%) and relative importance of factors on responses were found. Optimum conditions obtained from genetic algorithm were: moisture content of feed-mix = 57.43% (wb), baking temperature = 151.4°C, baking time = 4.35 h, height of mix = 2.9 cm.

Introduction

Chhana podo is the only traditional baked dairy product in India and comprises chhana (Indian cottage cheese), sugar and semolina/refined wheat flour as essential ingredients (Figure 1). Based on local preferences, it may include cloves, cardamoms and nuts. This *chhana* cake finds its origin in Odisha and it is popular mainly in regions of eastern India. It closely resembles a north Indian traditional dairy product "milk-cake" in appearance, which is prepared from whole milk by heat desiccation in contrast with heat-acid coagulation employed for *chhana podo* (Karwasra *et al*., 2001). Most of these milk-based sweetmeats serve as a concentrated source of milk solids; they provide variety to the diet and enhance nutrition at the same time; they are high or intermediate moisture products and hence require refrigerated storage for extension of their limited shelf-life (Aneja *et al*., 2002).

Figure 1. *Chhana podo* - The only baked traditional dairy product in India

As reported by Ghosh *et al.* (2002), traditionally, *chhana podo* has been preferred as an offering to Lord Jagannath in Puri temple for hundreds of years; local sweetmeat-makers say that the product was invented by Mr. Kelu Behera in Pahel; records are also available stating that it was independently produced by the Pratihari family. *"Podo"* in Oriya means burning; this substantiates the term used to define the product, since *chhana podo* is a baked product. Traditionally, it is made by smoldering *chhana*-sugar mix wrapped in sal leaves or other large leaves on slow fire. It is also possible that the name has come from Podomari village in Ganjam district of Odisha. Kumar *et al.* (2002) described traditional methods of production as "small-scale non-standardized methods under highly unhygienic conditions". A survey conducted in 2010 revealed that *chhana podo* was being sold in markets of Odisha at 100 - 130 INR per kg while the price in Kolkata and regions of Midnapore was 140 - 180 INR per kg. Prices varied in different regions in and around West Bengal and Odisha. In Kolkata most sweetmeat-makers did not produce *chhana podo* themselves, but got the product supplied from few other sweetmeat-makers who specialized in *chhana podo* production (Mukhopadhyay, 2012).

The technology for large-scale production of *chhana podo* was developed by National Dairy Development Board, Anand. However, production of *chhana podo* is still a cottage industry and hence there are region specific differences in product

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quality. In addition, there is often batch-to-batch variation in product quality in terms of physical as well as sensory characteristics. Ghosh *et al*. (1998) stated that *chhana podo* should have a light brown color, cooked flavor and a cake-like soft spongy body. Ghosh *et al.* (2002) attempted characterization of market samples in Odisha with respect to cake height, physical appearance and sensory characteristics as judged by panelists from National Dairy Research Institute (NDRI), Bangaluru, India; the product varied greatly in all characteristics from district to district. Kumar *et al.* (2002) enumerated the functions of different ingredients; fat in standardized milk, semolina, sugar and water and varied the levels of these ingredients to study their effect on sensory and textural characteristics of *chhana podo.* Optimization of levels of ingredients was based on sensory evaluation by panelists from NDRI Bangaluru. The most desirable product had *chhana* from milk (fat: 4.5%), 35% sugar, 5% semolina and 30% added water (all ingredients were added by weight of *chhana*). Ghosh *et al.* (1998) studied two baking temperature-time combinations, 250°C for 45 min and 200°C for 65 min, and reported the latter to be optimum whereas Dash *et al.* (1999) produced *chhana podo* in the laboratory and reported 150°C for 90 min as optimum. Kumar *et al*. (2002) reported the optimum baking condition as 200°C for 50 min.

While available literature on *chhana* production is substantial, the same on *chhana podo* production is scanty; the latter suffer from some shortcomings such as: importance of initial moisture content of the feed-mix was ignored, no objective output parameters (moisture content, hardness, expansion ratio, color etc.) were used in deciding the desirability of the final product and/or the optimum values of input parameters (moisture content of feed-mix, baking temperature, baking time etc.) and optimization was not done using any numerical optimization tool.

Genetic Algorithm (GA) is a population based probabilistic, iterative search and optimization technique that imitates the natural selection process as postulated by Darwin. A sub-field of evolutionary algorithms and computing, it is a stochastic optimization method based on concepts of natural selection and genetics and has been successfully applied to numerical optimization problems (Holland, 1975; Goldberg, 1989). For optimization using GA, one must be able to predict responses for various combinations of factors. For such prediction either empirical equations or neural networks can be used. Empirical equations are developed to find relationships between factors and responses since existing physical and chemical laws are insufficient to quantify the changes (Das, 2005). Artificial neural network (ANN) is a well-known tool for solving complex, non-linear biological systems (De Baerdemaeker and Hashimoto, 1994) and can give reasonable solutions even in extreme cases or in the event of technological faults (Lin and Lee, 1995). ANN is a collection of interconnecting computational elements, which function like neurons in the biological brain and can relate input and output parameters without any prior knowledge of the relationship between them (Izadifar *et al*., 2007). It is a data driven imbibing technology (Cheng and Titterington, 1994; Pham and Xing, 1995; Stern, 1996; Leondes, 1998; Kay and Titterington, 1999; Platei *et al*., 2000; Sugiyama and Ogawa, 2001; Raudys, 2001) and successfully models multivariate, non-linear data with discontinuous regions (Suryanarayana *et al*., 2008). Hence, ANN finds wide application in capturing and representing complex input/output relationships and learns directly from pairs of input and their corresponding output. After the learning / training stage, the network can be used to predict outputs from a different combination of inputs not used in training but within the limits / ranges in which the network was trained (Yegnyanarayana, 2000; Rajasekaran and Pai, 2004). A trained ANN gives a higher degree of fit between actual and predicted data (Yegnyanarayana, 2000; Rajasekaran and Pai, 2004; Pratihar, 2008). Among several available learning algorithms, back-propagation has been the most widely implemented learning algorithm of all ANN paradigms (Haofei *et al*., 2007). Over the last decade, ANNs have found wide application in several food processing areas such as drying technologies (Kaminski *et al*., 1998; Sreekanth *et al*,. 1998; Chen *et al.*, 2000), baking (Cho and Kim, 1998), fermentation (Aires-de-Sousa, 1996; Teissier *et al*., 1997), postharvest (Morimoto *et al*., 1997a), food rheology (Ruan *et al.*, 1995), thermal processing (Sablani *et al.*, 1997a, 1997b; Afaghi, 2000; Afaghi *et al.*, 2000; Chen and Ramaswamy, 2000). Both ANN and GA are extremely robust mathematical optimization techniques used for solving multi-objective problems (Deb, 2001; Rajasekaran and Pai, 2004). Hashimoto (1997) introduced application of ANN and GA to agricultural systems. Morimoto *et al.* (1997b) developed an ANN-GA integrated technique for optimal control of fruit storage process.

In view of the gaps in available literature on *chhana podo* production as mentioned above, this project was undertaken to develop a method for optimization of process parameters with the objectives to study the relationship between independent (input) and dependent (output) variables using empirical equations and/or ANN as well as to optimize the process parameters for production of *chhana podo* using GA.

Material and Methods

Factors, responses and experimental design

For optimization of process parameters, independent variables (factors), dependent variables (responses) and corresponding ranges of factors were identified heuristically. Factors and their ranges were as follows (method of measurement is given in parentheses alongside): moisture content (MC) of feed-mix (X_1): 52.5 – 62.5% (wb) [Infrared Moisture Analyzer: MX – 50, AandD Company Limited, Japan, ± 0.01% (wb)], baking temperature (X_2): 60 – 180°C [temperature indicator: SD Instruments Pvt. Ltd., India, ± 0.1°C], baking time (X_3): 1 – 9 h [stopwatch: MS83301A, Shanghai Diamond Stopwatch Company, China, ± 0.1 s] and height of feed-mix (X_4): 1 – 5 cm [ruler, ± 0.1 cm]. Responses were: MC of *chhana podo* (% wb) (Y_1), crust hardness (g) (Y_2), crumb hardness (g) (Y_3), expansion ratio (Y_4), crust whiteness index (Y_5), crust yellowness index (Y_6), crust tint (Y_7), crumb whiteness index (Y_8), crumb yellowness index (Y_9) and crumb tint (Y_{10}). Rotatable central composite design (RCCD) was done for four factors using MATLAB® (The MathWorks, Version 7.10.0.499). Out of thirty one experiments, seven were done at centre-point data (Myers, 1971). Experiments were conducted in random order; randomization was performed using MATLAB.

Measurement of responses

MC of *chhana podo* was measured in a calibrated Infrared Moisture Analyzer which gave MC of the sample directly. Hardness was analyzed using a texture analyzer (TA-XT2i Texture Analyzer, Sun Microsystems, USA). Samples of 1 cm in height were cored out using a 1-cm diameter cylindrical corer. Crust hardness was measured from samples of 1 cm in height with the crust whereas crumb hardness was measured from samples cored out from the interior of the baked *chhana podo*. Each sample (cooled to room temperature) was compressed to 70% of its original height, and peak force experienced by the cross head of the texture analyzer probe was taken as hardness. For each reading, five samples were analyzed and their mean was reported. Expansion ratio (ER) was determined to quantify change in volume and was defined as the ratio of final volume of *chhana podo* after baking and initial volume of feed-mix in tray. Mukhopadhyay (2012) devised an alternative method for volume estimation of baked *chhana podo* using two-dimensional image analysis, since *chhana podo* is a high MC, wettable product whose volume cannot be measured using traditional water displacement method. Samples were analyzed for crust and crumb color; color for each sample was measured using a colorimeter (CM-5 Spectrophotometer, Konica Minolta, Japan). L^*, a^* and b^* values were noted (CIE Publication, 1986). All measurements were made in triplicate and mean values were reported. CIE tristimulus values, whiteness index, yellowness index and tint were calculated according to ASTM E-313.

Chhana preparation and analysis of chhana

Jagtap and Shukla (1973) and De (1980) reported that a minimum fat content of 4% in cow milk was essential to obtain *chhana* of satisfactory texture; hence, branded market milk Amul Taaza® (Sumul Dairy, Surat, Gujarat, India) containing fat - 3.0%, SNF - 8.5%, and Amul Gold® (Surat District Co-operative Milk Producers' Union Limited, Surat, Gujarat, India) containing fat - 6.0%, SNF - 9.0% were mixed in the ratio 1:1 (v/v) to ensure a fat percentage of 4.5%. After combining the two varieties of milk, the following measurements were made; MC (gravimetric method - AOAC, 1997), density (by lactometer: Scientific International Pvt. Ltd., India, + 0.5 lr, range 0 - 40), titrable acidity as % lactic acid (Lane-Eynon method - Ranganna, 1987) and fat content (by Gerber method - IS: 1224, 1997).

Preparation of chhana involves heating of milk to near-boiling temperatures followed by acid-coagulation of the milk. In this study, citric acid was used as the coagulating agent; 2.6 g of citric acid was dissolved in 200 ml of distilled water, and maintained at -8 to -10°C. In a stainless steel container, milk was heated, with its temperature being monitored using a thermometer. When the temperature of the milk reached 95°C, the citric acid solution was added and the contents were gently stirred. The residence time for coagulation was fixed at 1 min. After the set duration, the coagulated mixture was strained using a muslin cloth; chhana was retained for chhana podo production whereas, the whey was discarded. *Chhana* thus prepared was used for production of *chhana podo* (Figure 2).

Chhana podo *production*

Since MC of feed-mix was an independent variable in the study; feed-mix composition for *chhana podo* was fixed on dry solids basis. From preliminary experiments, roasted semolina was chosen as the additional ingredient and the ratio was set at as given in the formula

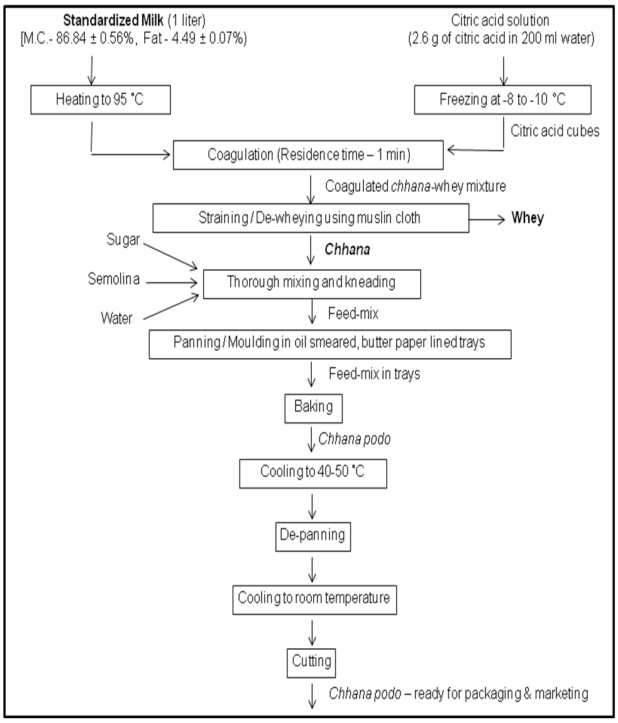

Figure 2. Process flowchart for *chhana podo* production from milk

$$C_d : I_d : S_d : w :: 1 : 0.1 : 0.5 : w$$

i.e., 0.1 kg of roasted semolina (db) and 0.5 kg sugar (db) were added per kg of *chhana* (db) respectively. C_d : Chhana dry solids, I_d: Additional ingredient, dry solids, S_d : Sugar dry solids and w: Total water (water from *chhana* + water from additional ingredient + added water)

A Microsoft Excel sheet was prepared to calculate mass of roasted semolina, sugar and water to be added to achieve desired MC in feed-mix. Following were kept as input: MC of *chhana*, mass of *chhana*, MC of sugar, MC of roasted semolina and desired MC of feed-mix. The design of experiment gave the desired MC of mix for each experimental run. *Chhana podo* feed-mix comprising chhana, sugar, roasted semolina and added water (if any) was kneaded in a household mixer (HR7625/70 Food Processor, Koninklijke Philips Electronics, India) for 4-5 min to obtain a smooth batter. MC of feed-mix (X_1) was recorded. The baking oven (SD Instruments Pvt. Ltd., India) was preheated to the desired temperature (X_2) for the tray to be kept for the required baking time (X_3). The stainless steel tray (15.2 cm X 15.2 cm X 7.6 cm) was lined with butter paper before pouring the feed-mix into it up to the desired level. A needle was dipped into the feed-mix and removed; the height of the feed-mix was determined by the level to which the feed-mix adhered to the surface of the needle. This was done at five points inside the tray (four readings at four corners and one reading at the centre) and mean value was reported as height of feed-mix (X_4). At the end of the baking time, the tray was taken out and inverted after a few minutes to de-pan the chhana podo. Subsequent analysis was carried out to report the values of responses. The study was conducted in Agricultural and Food Engineering Department, Indian Institute of Technology Kharagpur.

Empirical equation development

Empirical equations in terms of dimensionless, coded factors *(x)* and real responses *(Y)* were developed to model the data. For each response; relative deviation percent (Rd) was calculated, statistical test of significance of the equation, test of significance for lack of fit were conducted and relative importance of terms was found (Das, 2005). A code was written in MATLAB® for the above calculations.

Modeling of independent and dependent parameters using neural network

A Feed Forward Back Propagation Neural Network (FFBPNN) was constructed with four neurons in input layer, one hidden layer and ten neurons in output layer. There is no general criterion about deciding the number of neurons in hidden layer and there are many ways of doing it, one such way is the use of the formula (Kasabov, 1998)

$h \geq (p - 1) / (n + 2)$, where h: minimum number of hidden layer neurons, p: number of training sets fed to the network, and n : number of input layer neurons in the network.

The hidden and the output neurons were assumed to have log-sigmoid transfer function as described by Pratihar (2008). Gradient descent method was used for training the network (Yegnyanarayana, 2000; Rajasekaran and Pai, 2004). ANN parameters were used to find the degree of fit between factors and responses and relative importance of factors on responses. Figure 3 gives the computation steps in FFBPNN architecture.

Genetic algorithm as a tool for optimization

Optimization of process parameters was done using genetic algorithm using the trained FFBPNN model. Factors were coded between -1 and +1 whereas responses were coded between 0 and +1. Tournament selection was used as a reproduction scheme (Rajasekaran and Pai, 2004). Mating pairs (parents) were selected randomly and single point crossover operator was employed (Goldberg, 1989). Since, evaluation is performed after generation of new prospective solutions in a population; GA may generate a large number of unfeasible solutions before the sought solution is found. Penalty functions were introduced to solve this constrained optimization

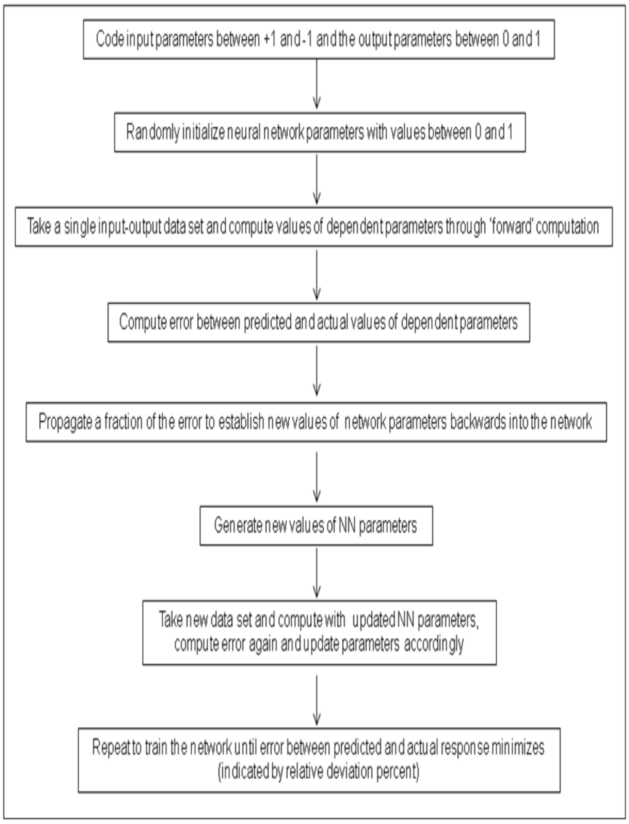

Figure 3. Computation steps in FFBPNN

problem. This is the most popular approach and uses functions designed to penalize unfeasible solutions by reducing their fitness values in proportion to their degrees of constraint violation; however, there are no general rules for designing penalty functions (Michalewicz *et al*., 1996; Smith and Coit, 1997; Deb, 2000).

GA parameters were as follows

Precision (a_p) for each factor;

For $X_1 = 0.1$, $X_2 = 0.5$, $X_3 = 0.1$, $X_4 = 0.05$

Total string length *(M)* = 22, number of population strings generated (N_p) = 27 (Goldberg, 1989), learning rate *(L)* = 0.6 (by checking convergence using trial and error), crossover rate *(cr)* = 0.8 and probability of mutation *(fm)* = 0.05 (Rajasekaran and Pai, 2004). Based on our experience and understanding of the process, the fitness function was designed to maximize Y_1, Y_4, Y_6, Y_7, Y_9 and Y_{10} and to minimize Y_2, Y_3, Y_5 and Y_8. The fitness function used is given as the following formula

$$F = y_1 + \frac{1}{1+y_2} + \frac{1}{1+y_3} + y_4 + \frac{1}{1+y_5} + y_6 + y_7 + \frac{1}{1+y_8} + y_9 + y_{10}$$

y_1 to y_{10} are the coded values of responses corresponding to Y_1 to Y_{10} respectively.

The fitness function was designed as shown in the above formula keeping in mind the general attribute preferences for the product available in the market and intuitive sense. A higher MC in the product (Y_1) would yield a soft, moist product; higher expansion ratio (Y_4) would ensure a fluffy product and give economic gains to the producer; greater crust yellowness index (Y_6), crust tint (Y_7), crumb yellowness index (Y_9) and crumb tint (Y_{10}) would yield the desirable cooked color in the product. Crust and crumb hardness (Y_2 and Y_3 respectively) were minimized for a soft, spongy product; and crust and crumb whiteness indices (Y_5 and Y_8 respectively) were minimized for a cooked, caramelized product appearance. Constraints for some of the responses (viz. Y_1, Y_2, Y_3 and Y_4) were applied as penalty functions to the above fitness / objective function. The penalty functions were introduced in normalized form as given below ij (Rajasekaran and Pai, 2004).

For constraint, $y_i lower < y_i < yiupper$

$$P_i lower = |(y_i / y_i lower) - i| \quad \text{when } y_i < y_i lower$$
$$= 0 \quad \text{otherwise}$$
$$P_i upper = |(y_i / y_i upper) - i| \quad \text{when } y_i > y_i upper$$
$$= 0 \quad \text{otherwise}$$

y_i = Coded value of ith response, i = 1 to 4
y_i *lower* = Lower bound of i[th] response in coded form
y_i *upper* = Upper bound of i[th] response in coded form
P_i *lower* = Penalty function of i[th] response for lower bound
P_i *upper* = Penalty function of i[th] response for upper bound

Constraints used;

For $Y_1 \rightarrow$ lower bound = 45, upper bound = 52,
For $Y_2 \rightarrow$ lower bound = 150, upper bound = 170,
For $Y_3 \rightarrow$ lower bound = 110, upper bound = 130,
For $Y_4 \rightarrow$ lower bound = 0.9, upper bound = 1.3,

Above constraints were selected based on data collected from market samples as well as our experience and understanding of the process. A modified fitness function was constructed such that it would decrease whenever any of the constraints got violated, thus, population strings with highest fitness values would be retained in each cycle.

Modified fitness function (F_{new}) was given in the formula

Table 1. Factors and responses for RCCD – experimental data

Expt. No.	Actual RCCD conditions: MC of feed-mix (% wb) [X_1]	Baking temp. (°C) [X_2]	Baking time (h) [X_3]	Height of feed-mix (cm) [X_4]	Y_1 (% wb)	Y_2 (g)	Y_3 (g)	Y_4	Measured			Computed from L*, a* and b*			Measured			Computed from L*, a* and b*		
									L*	a*	b*	Y_5	Y_6	Y_7	L*	a*	b*	Y_8	Y_9	Y_{10}
1	54.08	150	7	2	44.16	267.8	106.2	0.93	33.2	5.75	5.41	-99.05	51.76	-32.95	52.3	16.23	33.44	-343.42	134.98	-92.87
2	57.1	120	9	3	50.26	193.1	114	0.93	57.08	14.81	34.45	-336.06	130.13	-83.27	34.23	9.4	10.57	-186.46	86.87	-58.43
3	55.9	120	5	5	43.92	221.8	134.7	0.94	42.78	13.4	18.72	-261.49	113.07	-78.36	75.44	6.02	25.96	-214.07	91.9	-37.66
4	60.25	150	7	4	47.35	225.2	105.6	0.74	34.08	5.8	5.59	-100.25	52.2	-32.91	59.43	13.08	30.23	-303.12	119.97	-71.86
5	54.09	150	3	2	47.44	198.9	144.1	1.07	83.31	11.74	17.44	-105.05	71.51	-39.91	74.73	5.38	24.86	-207.91	89.37	-35.38
6	54.08	150	7	4	41.34	168.3	108.4	0.91	30.37	4.93	4.21	-82.16	44.38	-28.84	56.88	14.17	33.19	-330.44	127.89	-80.37
7	49.81	120	5	3	46.4	202.4	176	1.05	42.46	11.07	17.16	-247.41	104.97	-67.15	65.8	11.27	31.78	-292.53	115.14	-62.36
8	58.21	120	5	3	53.35	197.2	126.7.0	0.77	65.81	13.11	37.36	-324.88	124.83	-71.96	79.56	4.36	22.6	-169.82	80.19	-29.31
9	58.81	180	4	3	48.29	211.5	109.7	0.95	27.79	7.38	6.7	-139.6	69.77	-48.24	69.67	9.44	28.82	-257.27	105.11	-52.07
10	59.3	150	3	2	52.07	200	101	0.9	42.78	13.4	18.72	-261.49	113.07	-78.36	75.44	6.02	25.96	-214.07	91.9	-37.66
11	59.3	150	3	4	53.33	173.2	149.2	0.77	54.97	16.58	35.5	-345.3	135.42	-92.4	80.42	0.87	17.66	-122.81	63.89	-16.93
12	58.13	120	5	1	27.25	245.6	113.7	0.5	37.51	10.23	11.75	-192.22	89.46	-60.28	53.98	14.51	29.61	-316.56	125.77	-81.6
13	60.25	150	7	2	43.15	246.2	118.6	0.75	30.79	7.69	8.02	-155.21	74.59	-49.35	48.75	16.18	29.23	-329.44	132.77	-93.75
14	54.09	150	3	4	50.8	256.7	114.2	1.23	47.36	15.08	24.21	-296.97	123.67	-86.09	79.83	2.44	20.75	-153.24	73.77	-23.19
15	58.81	90	3	4	55.13	-	-	-	83.46	-0.18	17.08	-107.04	59.86	-13.69	88.32	0.07	11.8	-40.62	42.53	-9.53
16	58.13	120	1	3	56.26	-	-	-	87.6	-0.7	10.7	-32.62	38.66	-7.22	85.92	-0.72	14.72	-76.39	51.6	-10.43
17	59.75	90	7	2	47.41	-	-	-	80.02	-0.47	22.62	-171.62	75.6	-17.76	83.69	-0.58	14.59	-82.56	52.27	-10.85
18	59.75	90	3	2	50.63	-	-	-	83.27	-1.26	14.72	-85.51	52.26	-9.54	85.5	-0.73	12.33	-54.85	44.54	-8.59
19	53.93	90	7	2	46.78	-	-	-	77.91	2.15	25.51	-203.65	85.72	-26.74	82.6	0.11	14.85	-88.43	54.12	-12.65
20	59.75	90	7	4	49.98	-	-	-	81.04	-1.04	18.72	-131.78	64.76	-13.35	85.65	-0.73	13.65	-67.09	48.52	-9.61
21	58.3	60	5	3	51.38	-	-	-	91.56	-1.89	23.34	-132.98	70.18	-13.57	88.91	-2.54	14.63	-66.1	48.64	-6.44
22	53.93	90	3	2	51.35	-	-	-	81.44	-0.37	19.06	-133.16	66.04	-15.08	85.79	-0.5	11.95	-50.19	43.43	-8.73
23	55.32	90	3	4	53.23	-	-	-	83.54	-0.94	20.19	-136.19	67.39	-14.37	86.31	-1.01	12.44	-53.44	44.34	-8.05
24	53.93	90	7	4	49.95	-	-	-	85.42	-0.21	12.96	-61.01	46.96	-10.16	78.98	-0.77	20.75	-158.54	71.34	-15.81
25	56.55	120	5	3	49.87	149.9	119.4	0.91	41.94	14.64	23.03	-307.73	127.06	-90.76	69.94	9.39	29.04	-258	105.27	-51.96
26	56.8	120	5	3	50.41	160.6	105.8	0.89	40.45	14.9	24.03	-321.8	131.46	-95.49	70.04	9.59	29.15	-258.24	105.61	-52.55
27	58.13	120	5	3	51.88	156.2	112.6	0.9	33.64	11.29	12.99	-225.52	102.28	-72.73	70.62	9.28	29.3	-257.46	105.13	-51.48
28	57.3	120	5	3	50.01	160.6	113.7	0.9	41.66	15.78	22.05	-297.44	127.15	-94.59	68.95	9.41	30.11	-270.21	107.95	-53.5
29	58.1	120	5	3	51.78	161.1	113.1	0.91	42.87	15	22.99	-303.12	126.38	-90.74	70.09	9.61	28.78	-255.1	104.9	-52.26
30	57.1	120	5	3	51.11	154.4	112.7	0.92	40.96	14.55	22.99	-311.31	128.08	-91.88	69.82	9.43	29.11	-258.98	105.53	-52.2
31	57.4	120	5	3	51.45	161.1	111.4	0.92	40.95	14.53	22.79	-311.01	127.9	-91.55	68.94	9.34	31.21	-271.73	108.43	-54.18

$$F_{new} = F \{1 - K (\sum P_i lower + \sum P_i upper) \}$$

K : Parameter whose value is selected depending on required influence of constraint violations, found to be 10 in most cases (Rajasekaran and Pai, 2004)

The modified fitness function was maximized and root mean square error (RMSE) was computed. By trial and error method, it was seen that convergence was achieved (RMSE approached zero) within 50 generations in a GA cycle when total number of GA cycles was 1000.

Results and Discussion

Analysis of milk and chhana

Analysis of the milk and channa show that the density of milk was 1029 ± 5 kg.m^{-3}, titrable acidity of milk was 0.168 ± 0.005% (as lactic acid), MC of milk was 86.84 ± 0.56% (wb), fat content of milk was 4.49 ± 0.007% and MC of *chhana* was 57.77 ± 1.77% (wb).

Modeling of independent and dependent parameters

Empirical equation development

Table 1 shows RCCD runs at different levels of factors with actual conditions and corresponding responses. Experiment numbers 15 to 24 had to be discarded since these runs yielded severely under-baked *chhana podo* making it impossible to measure hardness and to calculate expansion ratio. Even for the runs with baking time of 7 h,a baking temperature of 90°C was too low for any baking/cooking to take place. This shows that a combination of baking time and temperature is important for proper baking. Majority of the RCCD results show that this product, unlike other baked products, contracted on baking (i.e., ER < 1.0). Although this is a baked product, the primary raw material is *chhana* as opposed to wheat flour in most baked goods. Bakery products are often classified as yeast leavened goods, chemically leavened goods, air leavened goods and partially leavened goods. In either case, the food structure must be such that it can trap the leavened gas and hold its structure (coagulation and fixing of the matrix by the application of heat). Wheat contains gliadin and glutenin which form the principal functional protein, gluten; gluten has the unique property of forming an elastic dough when moistened and worked upon by mechanical action (Potter and Hotchkiss, 1998). *Chhana podo* is made up of different ingredients, chhana, which forms the major fraction is incapable of holding such a leavened structure. During baking, it was observed that the structure leavened (up to triple the initial volume) but collapsed subsequently on cooling.

Quadratic equations were fitted for remaining twenty one data sets (Table 2). The relationships between real values of factors *(X)* and corresponding dimensionless, coded values *(x)* are given in the following equations

For X_1 → $x_1 = (X_1 – 55.03) / 2.61$
For X_2 → $x_2 = (X_2 – 150) / 15$
For X_3 → $x_3 = (X_3 – 6) / 1.5$

Table 2. Quadratic equations for responses Y_1 to Y_{10}

Y	Empirical equation (quadratic)
Y_1	$Y_1 = -1.837 - 0.0348x_1 + 44.0506x_2 + 47.1657x_3 + 0.0467x_4 + 0.8256x_1^2 + 22.1228x_2^2 + 37.2715x_3^2 - 3.6377x_4^2 - 1.1488x_1x_2 - 0.3875x_1x_3 + 0.6478x_1x_4 + 48.3523x_2x_3 - 2.1016x_2x_4 - 0.3475x_3x_4$ (Rd = 1.214%) Test of significance: Fo_{Reg} (24.234) = F, $p_{Reg} = 4.07 \times 10^{-4}$ → Factors affect the response with a probability of $(1 - 4.07 \times 10^{-4})$ Lack of fit: Fo_{lof} (9.253) = F_{lof}, $p_{lof} = 2.87 \times 10^{-2}$ → Lack of fit is significant with a probability of (2.87×10^{-2}), model does not fit the data.
Y_2	$Y_2 = 198.7123 - 25.0243x_1 + 22.3554x_2 - 8.8992x_3 - 21.3304x_4 + 16.4712x_1^2 + 0.7058x_2^2 - 6.1444x_3^2 + 18.7284x_4^2 - 17.1733x_1x_2 + 8.3151x_1x_3 + 0.8721x_1x_4 - 11.9269x_2x_3 - 5.6839x_2x_4 - 14.2620x_3x_4$ (Rd = 5.406%) Test of significance: Fo_{Reg} (2.292) = F, $p_{Reg} = 1.57 \times 10^{-1}$ → Factors do not affect the response with a probability of 1.573×10^{-1} Lack of fit: Fo_{lof} (183.901) = F_{lof}, $p_{lof} = 3.90 \times 10^{-5}$ → Lack of fit is significant with a probability of (3.90×10^{-5}), model does not fit the data.
Y_3	$Y_3 = 64.8560 - 15.0147x_1 + 29.2948x_2 + 29.1543x_3 - 5.7247x_4 + 10.3690x_1^2 + 17.7440x_2^2 + 28.0023x_3^2 + 3.7531x_4^2 - 2.4838x_1x_2 + 0.1218x_1x_3 + 6.2659x_1x_4 + 33.0769x_2x_3 - 2.6570x_2x_4 - 3.1513x_3x_4$ (Rd = 5.387%) Test of significance: Fo_{Reg} (1.495) = F (3.956), $p_{Reg} = 3.24 \times 10^{-1}$ → Factors do not affect the response with a probability of 3.236×10^{-1} Lack of fit: Fo_{lof} (69.878) = F_{lof} (6.608), $p_{lof} = 4.01 \times 10^{-3}$ → Lack of fit is significant with a probability of (4.01×10^{-3}), model does not fit the data.
Y_4	$Y_4 = 0.1242 - 0.0714x_1 + 0.8206x_2 + 0.8074x_3 + 0.0187x_4 - 0.0153x_1^2 + 0.3984x_2^2 + 0.6612x_3^2 - 0.0522x_4^2 - 0.0116x_1x_2 + 0.0335x_1x_3 - 0.0290x_1x_4 + 0.8529x_2x_3 - 0.0455x_2x_4 - 0.0037x_3x_4$ (Rd = 3.145%) Test of significance: Fo_{Reg} (6.227) = F, $p_{Reg} = 1.67 \times 10^{-2}$ → Factors affect the response with a probability of $(1 - 1.671 \times 10^{-2})$ Lack of fit: Fo_{lof} (172.155) = F_{lof}, $p_{lof} = 4.60 \times 10^{-5}$ → Lack of fit is significant with a probability of $(1 - 4.60 \times 10^{-5})$, model does not fit the data.
Y_5	$Y_5 = -108.2028 - 61.1422x_1 + 74.7430x_2 - 13.2973x_3 - 16.1074x_4 + 23.6363x_1^2 - 6.1729x_2^2 - 43.6897x_3^2 + 22.9577x_4^2 - 37.3800x_1x_2 + 10.152x_1x_3 + 15.9720x_1x_4 - 26.4755x_2x_3 - 8.3950x_2x_4 + 31.5071x_3x_4$ (Rd = 5.445%) Test of significance: Fo_{Reg} (9.934) = F, $p_{Reg} = 4.92 \times 10^{-3}$ → Factors affect the response with a probability of $(1 - 4.9 \times 10^{-3})$ Lack of fit: Fo_{lof} (0.359) = F_{lof}, $p_{lof} = 5.75 \times 10^{-1}$ → Lack of fit is insignificant with a probability of 5.75×10^{-1}, model fits the data.
Y_6	$Y_6 = -44.5506 + 22.8020x_1 + 67.7515x_2 + 102.8586x_3 + 2.9010x_4 - 9.4450x_1^2 + 48.9039x_2^2 + 91.3918x_3^2 - 7.3351x_4^2 + 13.4915x_1x_2 - 1.3008x_1x_3 - 4.9612x_1x_4 + 111.3491x_2x_3 + 1.6525x_2x_4 - 9.4412x_3x_4$ (Rd = 2.888%) Test of significance: Fo_{Reg} (17.368) = F (3.956), $p_{Reg} = 1.05 \times 10^{-3}$ → Factors affect the response with a probability of $(1 - 1.05 \times 10^{-3})$ Lack of fit: Fo_{lof} (- 1.204) = F_{lof} (6.608), $p_{lof} = 1.00$ → Lack of fit is insignificant with a probability of 1.00, model fits the data.
Y_7	$Y_7 = 12.4620 - 25.1776x_1 - 27.1306x_2 - 56.1301x_3 - 3.6776x_4 + 12.3725x_1^2 - 25.2512x_2^2 - 51.3367x_3^2 + 6.2967x_4^2 - 15.9287x_1x_2 + 0.9097x_1x_3 + 4.8733x_1x_4 - 63.5239x_2x_3 - 2.7986x_2x_4 + 7.2431x_3x_4$ (Rd = 4.602%) Test of significance: Fo_{Reg} (12.717) = F, $p_{Reg} = 2.51 \times 10^{-3}$ → Factors affect the response with a probability of $(1 - 2.51 \times 10^{-3})$ Lack of fit: Fo_{lof} (0.192) = F_{lof}, $p_{lof} = 1.00$ → Lack of fit is insignificant with a probability of 1.00, model fits the data.
Y_8	$Y_8 = -272.5491 - 21.4150x_1 - 58.6925x_2 - 94.3246x_3 + 12.2674x_4 + 19.0720x_1^2 - 22.4736x_2^2 - 26.3028x_3^2 - 0.5127x_4^2 - 27.4294x_1x_2 - 1.5799x_1x_3 + 5.4619x_1x_4 - 79.1108x_2x_3 - 7.9282x_2x_4 - 10.3654x_3x_4$ (Rd = 4.246%) Test of significance: Fo_{Reg} (4.996) = F, $p_{Reg} = 2.88 \times 10^{-2}$ → Factors affect the response with a probability of $(1 - 2.88 \times 10^{-2})$ Lack of fit: Fo_{lof} (101.755) = F_{lof}, $p_{lof} = 1.64 \times 10^{-4}$ → Lack of fit is significant with a probability of $(1 - 1.64 \times 10^{-4})$, model does not fit the data.
Y_9	$Y_9 = 59.1695 + 6.1114x_1 + 65.8176x_2 + 81.1908x_3 - 4.9099x_4 - 5.2902x_1^2 + 30.4771x_2^2 + 46.6949x_3^2 + 0.4563x_4^2 + 7.7178x_1x_2 + 0.6014x_1x_3 - 1.9989x_1x_4 + 75.4913x_2x_3 + 2.1305x_2x_4 + 2.3587x_3x_4$ (Rd = 2.724%) Test of significance: Fo_{Reg} (6.335) = F, $p_{Reg} = 1.60 \times 10^{-2}$ → Factors affect the response with a probability of $(1 - 1.599 \times 10^{-2})$ Lack of fit: Fo_{lof} (176.350) = F_{lof}, $p_{lof} = 4.30 \times 10^{-5}$ → Lack of fit is significant with a probability of $(1 - 4.30 \times 10^{-5})$, model does not fit the data.
Y_{10}	$Y_{10} = -5.4693 - 5.5273x_1 - 68.4974x_2 - 89.5697x_3 + 6.9212x_4 + 4.5194x_1^2 - 31.7941x_2^2 - 50.9397x_3^2 - 1.5003x_4^2 - 7.1683x_1x_2 - 0.3790x_1x_3 + 2.0498x_1x_4 - 77.7227x_2x_3 - 2.9543x_2x_4 - 0.0006x_3x_4$ (Rd = 4.803%) Test of significance: Fo_{Reg} (10.179) = F, $p_{Reg} = 4.61 \times 10^{-3}$ → Factors affect the response with a probability of $(1 - 4.61 \times 10^{-3})$ Lack of fit: Fo_{lof} (333.71) = F_{lof}, $p_{lof} = 9.00 \times 10^{-6}$ → Lack of fit is significant with a probability of $(1 - 9.00 \times 10^{-6})$, model does not fit the data.

Table 3. Relative importance of independent variables

	Δy_1	Δy_2	Δy_3	Δy_4	Δy_5	Δy_6	Δy_7	Δy_8	Δy_9	Δy_{10}
X_1										
+1 0 0 0	0.716	-0.689	0.381	-0.061	-0.747	0.458	-0.094	0.153	-0.165	0.224
-1 0 0 0										
X_2										
0 +1 0 0	-0.901	-0.000	-0.077	-0.888	0.374	-0.590	0.921	-0.028	0.042	-0.056
0 -1 0 0										
X_3										
0 0 +1 0	-0.335	-0.466	-0.342	-0.002	0.738	-0.902	0.975	-0.865	0.842	-0.907
0 0 -1 0										
X_4										
+1 0 0 0	0.115	-0.965	-0.221	-0.487	0.647	-0.631	0.687	0.999	-0.997	0.957
-1 0 0 0										

For $X_4 \rightarrow x_4 = (X_4 - 3) / 1$

Although Rd was below 10% in all cases, which is considered to be a good fit (Das, 2005), lack of fit was significant for all responses except Y_6 and Y_7. Thus, only Y_6 and Y_7 could be modeled using quadratic equations. Cubic equations could not be fitted since the system of equations became indeterminate in relation to the number of experimental data available. Neural network modeling had to be adopted for prediction of responses since the relationship between factors and responses was required for optimization of process parameters.

Neural network modeling

FFBPNN was trained with 18 data sets chosen randomly and validated using the remaining three data sets; network was started with three neurons (obtained from second formula) in the hidden layer and was increased progressively and each time RMSE was computed. Convergence was obtained with nine neurons in the hidden layer. For each data set, the forward-backward propagation computation was carried out 5000 times to minimize error between calculated and actual values of responses. Rd was computed for each response and mean Rd was computed for training and validation sets. Rd of all responses in training phase except that of Y1 decreased considerably as compared to those obtained from the empirical model. Mean Rd (1.739%) was low in the training phase. To confirm that the ANN was indeed well-trained, three remaining data sets were used for validation. In the validation phase, mean Rd (1.845%) was in line with the mean deviation obtained during the training phase.

Table 4. GA output of twenty strings with highest fitness values

String no.	X_1 (% wb)	X_2 (°C)	X_3 (h)	X_4 (cm)	Fitness Value (F)
316	57.43	151	4.35	2.94	7.575
596	56.60	150	4.55	3.19	7.572
44	57.10	150	4.55	3.06	7.553
10	56.27	149	4.55	3.19	7.549
519	55.28	145	4.74	3.19	7.540
5	56.60	151	4.35	3.06	7.528
588	56.44	150	4.35	3.19	7.518
319	56.27	150	4.35	3.06	7.495
487	55.78	140	5.13	3.06	7.409
304	57.60	151	4.35	3.19	7.405
22	56.94	149	4.74	3.19	7.400
345	56.27	150	4.74	3.19	7.387
229	55.78	150	4.55	3.19	7.380
515	55.94	152	4.35	3.19	7.374
359	57.27	151	4.55	2.94	7.374
65	54.95	149	4.16	3.32	7.374
436	55.28	153	3.77	3.45	7.364
516	54.95	150	4.16	3.45	7.340
595	55.61	156	3.77	3.45	7.350
499	55.78	153	3.97	3.58	7.347

Relative importance of independent variables with respect to different responses was computed as shown in Table 3. All results hold true within the range of the experiments of the present study. MC of *chhana podo* (Y_1) was dependent mostly on baking temperature (X_2) as given by the highest absolute value of $\Delta y_1 = 0.901$, then on MC of feed-mix (X_1), followed by baking time (X_3) and height of feed-mix (X_4). Negative sign indicates that increase in X_2 lowers Y_1. Same occurred with X_3 but with a lower dependence. However, increase in X_1 and X_4 increased value of Y_1. Hence, MC of *chhana podo* increased with increase in MC of feed-mix (X_1) and height of feed-mix (X_4) in tray, but decreased with increase in baking temperature and time. Interestingly, crust hardness of *chhana podo* (Y_2) did not depend on baking temperature (X_2) within the range of experiments conducted. It increased with decrease in height of feed-mix (X_4), MC of feed-mix (X_1) and baking time (X_3), in that order. Crumb hardness of *chhana podo* (Y_3) increased with increase in MC of feed-mix (X_1) but decreased with increase in baking time (X_3), height of feed-mix (X_4) and baking temperature (X_2), in that order. Expansion ratio (Y_4) increased with decrease in all the independent variables; order of dependence was as follows; $X_2 > X_4 > X_1 > X_3$. Crust whiteness index (Y_5) was mostly

Table 5. Relative deviation percent of predicted with respect to actual responses

Responses	Predicted Value	Actual Value	R_d (%)
Y_1	51.669	50.77	1.770
Y_2	174.56	170.67	2.282
Y_3	116.79	119.58	2.337
Y_4	1.2244	1.22	0.360
Y_5	-317.73	-306.08	3.806
Y_6	130.73	126.93	2.991
Y_7	-94.84	-90.94	4.284
Y_8	-283.93	-276.55	2.668
Y_9	112.35	108.03	4.002
Y_{10}	-46.89	-50.78	7.668

dependent on X_1 and increased with decrease in X_1 but increased with increase in X_2, X_3 and X_4; order of dependence for Y_5 was $X_1 > X_3 > X_4 > X_2$. Crust yellowness index (Y_6) was mostly dependent on X3 and increased with its decrease. It also increased with decrease in X_2 and X_4 but was more dependent on X_4 compared to X_2; however, it increased with increase in X_1. For crust tint (Y_7), order of dependence was $X_3 > X_2 > X_4 > X_1$. Y_7 *i*ncreased with increase X_2, X_3 and X_4 but decreased with increase in X_1. Crumb whiteness index (Y_8), crumb yellowness index (Y_9) and crumb tint (Y_{10}) were mostly dependent on X_4; Y_8 increased with increase in X_4 whereas Y_9 and Y_{10} followed an inverse relationship. Y_8 also increased with increase in X_1 but decreased with increase in X_2 and X_3, although effect of X_3 was more than that of X_2. Y_9 followed a direct relationship with X_2 and X_3, with X_3 being more dominant, but followed an inverse relationship with X_1. Crumb tint (Y_{10}) showed the same trend as crumb whiteness index (Y_8) with respect to X_1, X_2 and X_3 but decreased with increase in X_4. Order of dependence for Y_8, Y_9 and Y_{10} were the same as $X_4 > X_3 > X_1 > X_2$. There is no available literature on the effect of independent parameters on the attributes of the end product, hence it was not possible to compare or justify the results obtained in this study with any previous results.

Optimization of process parameters using genetic algorithm

Constrained optimization yielded different combinations of input conditions which could be used for the production of *chhana podo* at optimum conditions. Table 4 gives the first twenty strings with highest fitness values as obtained from the GA program. Optimum values of input parameters as obtained from GA were as follows: MC of feed-mix (X_1) = 57.43% (wb), baking temperature (X_2) = 151.4 °C, baking time (X_3) = 4.35 h, height of feed-mix (X_4) = 2.9 cm. To validate results of FFBPNN-GA, chhana podo was produced at optimum conditions in the laboratory and responses were measured (Table 5); the program was used to predict the responses. Input conditions and measured responses were as follows: Input conditions: X_1 = 57.46% wb, X_2 = 151 °C, X_3 = 4.35 h, X_4 = 3 cm; responses: Y_1 = 50.77 % wb, Y_2 = 170.67 g, Y_3 = 119.58 g, Y_4 = 1.22, Y_5 = -306.08, Y_6 = 126.93, Y_7 = -90.94, Y_8 = -276.55, Y_9 = 108.03, Y_{10} = -50.78. It was found that mean Rd of responses from that predicted by NN was 3.217% which was sufficiently low.

Conclusions

Production of *chhana podo* is a multi-variate process like most biological systems, out of ten responses, quadratic model could be fitted only for crust yellowness index (Y_6) and crust tint (Y_7) with Rd of 2.888% and 4.602% respectively. As expected, FFBPNN gave better prediction of responses as shown by low Rd values (Mean Rd for training = 1.739%, mean Rd for validation = 1.845%). Relative importance of factors on responses was successfully found. Optimum values of input parameters as obtained from GA were: MC of feed-mix (X_1) = 57.43% (wb), baking temperature (X_2) = 151.4°C, baking time (X_3) = 4.35 h, height of feed-mix (X_4) = 2.9 cm. *Chhana podo* was produced in the laboratory at conditions as close as possible to the above (because maintaining MC of feed-mix at the desired value is not practically possible; experimental MC of feed-mix (X_1) was 57.46% (wb)). Results showed that measured responses deviated from predicted values (as obtained from FFBPNN) by 3.217%, which was sufficiently low.

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