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 chhano 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).

As reported by Ghosh et al. (2002), traditionally, chhano 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 chhano-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 chhano 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...
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 Baerdemaecker 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; Prathihar, 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 ($Y_5$), crumb whiteness index ($Y_6$), crust yellowness index ($Y_7$), crumb yellowness index ($Y_8$) and crumb tint ($Y_9$). 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
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)

\[ h \geq \frac{p - 1}{n + 2} \]

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
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 $Y_2, Y_3, Y_4$ and $Y_8$. The fitness function used is given as the following formula

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

$y_1$ 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 ($Y_9$), crust tint ($Y_9$), crumb yellowness index ($Y_{10}$) 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 ($Y_4$ and $Y_8$ respectively) were minimized for a cooked, caramelized product appearance. Constraints for some of the responses (viz. $Y_1$, $Y_2$, $Y_7$ and $Y_8$) 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, $y_i^{lower} < y_i < y_i^{upper}$

$$P_i^{lower} = |(y_i/y_i^{lower}) - i|$$ when $y_i < y_i^{lower}

= 0$$ otherwise

$$P_i^{upper} = |(y_i/y_i^{upper}) - i|$$ when $y_i > y_i^{upper}

= 0$$ otherwise

$y_i$ = Coded value of $i^{th}$ 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 $Y_1$ lower bound = 45, upper bound = 52,
For $Y_2$ lower bound = 150, upper bound = 170,
For $Y_3$ lower bound = 110, upper bound = 130,
For $Y_4$ 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
\[ F_{\text{new}} = F \{1 - K (\sum P_{\text{lower}} + \sum P_{\text{upper}})\} \]

\( K \): 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 \(X_1\):

\[ x_1 = \frac{X_1 - 55.03}{2.61} \]

For \(X_2\):

\[ x_2 = \frac{X_2 - 150}{15} \]

For \(X_3\):

\[ x_3 = \frac{X_3 - 6}{1.5} \]
Table 2. Quadratic equations for responses $Y_1$ to $Y_{10}$

<table>
<thead>
<tr>
<th>Response</th>
<th>Equation</th>
<th>Test of significance: F, $p_{0.05}$</th>
<th>Factors affecting the response with a probability of (1 - 0.05) $^{2}$</th>
<th>Lack of fit: $F_{0.05}$, $p_{0.05}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y_1$</td>
<td>$y_1 = -1.037 - 0.0358 x_{1} + 4.42506 x_{2} + 47.167 x_{3} + 0.0367 x_{4} + 0.6292 x_{5} + 22.1226 x_{6} + 37.2715 x_{7}^{2} - 0.677 x_{8} x_{9} - 1.1466 x_{1} x_{2} - 0.3575 x_{1} x_{4} + 0.5476 x_{2} x_{4} + 45.0523 x_{3} x_{5} - 2.1616 x_{3} x_{7} - 0.2479 x_{3} x_{8} + 1.2142 x_{4} x_{7}$</td>
<td>$F_{0.05} = 4.234$</td>
<td>$p_{0.05} = 4.07 	imes 10^{-4}$</td>
<td>$F_{0.05} = 7.527 x_{2} x_{3} + 5.02 x_{4} x_{7}$</td>
</tr>
<tr>
<td>$Y_2$</td>
<td>$y_2 = 1.057 - 0.0234 x_{1} + 27.2654 x_{2} - 0.3912 x_{3} + 21.3934 x_{4} + 16.4712 x_{5}^{2} + 0.7058 x_{6}^{2} - 6.1444 x_{7} x_{8} + 18.7204 x_{7}^{2} + 17.1753 x_{8} x_{9} + 8.513 x_{8} + 0.8271 x_{9} + 11.0295 x_{9} x_{10} = 5.62 x_{9} x_{10}$</td>
<td>$F_{0.05} = 2.252$</td>
<td>$p_{0.05} = 1.57 	imes 10^{-3}$</td>
<td>$F_{0.05} = 13.291$</td>
</tr>
<tr>
<td>$Y_3$</td>
<td>$y_3 = 6.6569 - 16.1047 x_{1} + 20.2946 x_{2} + 20.1643 x_{3} + 5.7247 x_{4} + 10.3900 x_{5} + 17.7440 x_{6} + 26.0023 x_{7}^{2} + 3.753 x_{8}^{2} - 2.4356 x_{9} x_{10} + 0.1216 x_{1} x_{2} + 6.3659 x_{1} x_{4} + 33.0760 x_{2} x_{3} - 2.6576 x_{9} x_{10} = 3.1513 x_{9} x_{10}$</td>
<td>$F_{0.05} = 1.945$</td>
<td>$p_{0.05} = 3.24 	imes 10^{-1}$</td>
<td>$F_{0.05} = 6.6569$</td>
</tr>
<tr>
<td>$Y_4$</td>
<td>$y_4 = -0.142 - 0.0714 x_{1} + 0.8206 x_{2} + 0.5074 x_{3} + 0.0157 x_{4} + 0.3884 x_{5}^{2} + 0.6612 x_{6}^{2} - 0.0522 x_{7} - 0.0116 x_{8} x_{9} - 0.0335 x_{1} x_{10} - 0.0200 x_{1} x_{4} + 0.9259 x_{2} x_{4} - 0.0445 x_{2} x_{8} - 0.0037 x_{3} x_{8}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 12.227$</td>
</tr>
<tr>
<td>$Y_5$</td>
<td>$y_5 = -108.2098 - 61.1329 x_{1} + 73.7330 x_{2} - 13.2873 x_{3} + 16.1047 x_{4} + 23.6783 x_{5}^{2} - 6.7129 x_{6}^{2} - 43.6897 x_{7}^{2} + 22.9077 x_{7}^{2} - 37.3950 x_{8} x_{10} + 19.9720 x_{1} x_{4} + 26.4750 x_{3} x_{5} + 3.7950 x_{3} x_{5} + 52.6071 x_{4} x_{9}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 8.3590$</td>
</tr>
<tr>
<td>$Y_6$</td>
<td>$y_6 = -44.9059 + 22.9020 x_{1} + 0.7751 x_{2} + 102.6936 x_{3} + 2.9010 x_{4} + 9.4450 x_{5} + 46.9039 x_{6}^{2} + 91.3619 x_{7}^{2} - 7.3251 x_{8}^{2} + 13.4916 x_{9} + 1.3006 x_{10} = 4.9612 x_{1} x_{10} + 113.3451 x_{1} x_{10} + 1.9425 x_{2} x_{4}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 12.717$</td>
</tr>
<tr>
<td>$Y_7$</td>
<td>$y_7 = -12.8620 - 25.1776 x_{1} - 27.1305 x_{2} - 58.1510 x_{3} - 3.6776 x_{4} + 12.3725 x_{5}^{2} - 25.2912 x_{6}^{2} - 51.3367 x_{7}^{2} + 6.2697 x_{7}^{2} - 19.9267 x_{8} x_{9} + 0.0097 x_{8} x_{3} + 4.8735 x_{10} + 63.0230 x_{2} + 2.7066 x_{4} x_{9} + 7.2431 x_{9} x_{10}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 12.227$</td>
</tr>
<tr>
<td>$Y_8$</td>
<td>$y_8 = -37.5406 - 21.4115 x_{1} - 58.9655 x_{2} - 94.5246 x_{3} + 12.2674 x_{4} + 19.0720 x_{5}^{2} - 22.4736 x_{6}^{2} - 26.3025 x_{7}^{2} + 0.5162 x_{7} x_{8} - 27.4294 x_{7} x_{8} - 1.5796 x_{9} x_{10} + 5.4659 x_{9} x_{10} x_{2} - 79.1150 x_{2} x_{3} - 7.9225 x_{2} x_{3} x_{10}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 12.227$</td>
</tr>
<tr>
<td>$Y_9$</td>
<td>$y_9 = -54.5166 + 6.1114 x_{1} + 66.1977 x_{2} + 61.1508 x_{3} + 3.9009 x_{4} + 5.0002 x_{5}^{2} + 30.4771 x_{6}^{2} + 46.6849 x_{7}^{2} + 0.5600 x_{7}^{2} + 7.7178 x_{8} x_{10} + 0.0614 x_{10} x_{9} x_{10} + 70.4013 x_{3} x_{9} + 2.1305 x_{2} x_{4} + 2.8537 x_{9} x_{10}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 12.227$</td>
</tr>
<tr>
<td>$Y_{10}$</td>
<td>$y_{10} = -5.3583 - 5.5723 x_{1} - 68.4793 x_{2} - 85.5697 x_{3} x_{4} + 5.9212 x_{4} + 4.5140 x_{5} - 31.7631 x_{5}^{2} - 50.9397 x_{7}^{2} - 1.0003 x_{8} x_{2} - 7.1683 x_{8} x_{2} - 0.3790 x_{9} x_{2} + 2.0496 x_{10} x_{9} + 77.2227 x_{2} x_{3} x_{5} - 2.9645 x_{2} x_{4} - 0.0005 x_{10} x_{2}$</td>
<td>$F_{0.05} = 5.394$</td>
<td>$p_{0.05} = 4.92 	imes 10^{-3}$</td>
<td>$F_{0.05} = 12.227$</td>
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For $X_4 \rightarrow x = (X_4 - 3) / 1$

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. 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.

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 ($X_4$). 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; $X_4 > X_3 > X_1 > X_2$. Crust whiteness index ($Y_5$) was mostly

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<th>Fitness value</th>
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dependent on \( X_1 \) and increased with decrease in \( X_4 \), but increased with increase in \( X_2 \), \( X_3 \) and \( X_5 \), order of dependence for \( Y_4 \) was \( X_1 > X_4 > X_7 > X_5 \). Crust yellowness index (\( Y_4 \)) was mostly dependent on \( X_3 \) and increased with its decrease. It also increased with decrease in \( X_6 \) and \( X_7 \) but was more dependent on \( X_2 \) compared to \( X_6 \); however, it increased with increase in \( X_6 \). For crust tint (\( Y_5 \)), order of dependence was \( X_4 > X_1 > X_3 > X_2 \). Y4 increased with increase in \( X_3 \) and \( X_2 \) but decreased with increase in \( X_4 \). Crumb whiteness index (\( Y_6 \)), crumb yellowness index (\( Y_7 \)) and crumb tint (\( Y_8 \)) were mostly dependent on \( X_7 \); \( Y_5 \) increased with increase in \( X_9 \) whereas \( Y_7 \) and \( Y_{10} \) followed an inverse relationship. \( Y_5 \) also increased with increase in \( X_9 \) but decreased with increase in \( X_2 \) and \( X_6 \), although effect of \( X_8 \) was more than that of \( X_6 \). \( Y_7 \) followed a direct relationship with \( X_2 \) and \( X_6 \), with \( X_8 \) being more dominant, but followed an inverse relationship with \( X_9 \). Crumb tint (\( Y_8 \)) showed the same trend as crumb whiteness index (\( Y_5 \)) with respect to \( X_2 \), \( X_6 \) and \( X_9 \), but decreased with increase in \( X_7 \). Order of dependence for \( Y_{10} \) and \( Y_{10} \) were the same as \( X_2 > X_7 > X_7 > X_5 \). 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 (\( X_2 \)) = 4.35 h, height of feed-mix (\( X_3 \)) = 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, \( Y_4 \) = 122.91, \( Y_5 \) = -366.08, \( Y_6 \) = 126.93, \( Y_7 \) = -90.94, \( Y_8 \) = -276.55, \( Y_9 \) = 108.03, \( Y_{10} \) = -50.78. It was found that mean \( R_d \) 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 (\( Y_2 \)) and crust tint (\( Y_5 \)) with \( R_d \) of 2.888\% and 4.602\% respectively. As expected, FFBPNN gave better prediction of responses as shown by low \( R_d \) values (Mean \( R_d \) for training = 1.739\%, mean \( R_d \) 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 (\( X_3 \)) = 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.

**Acknowledgements**

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**References**


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