

MODELING OF EXTRUSION PROCESS USING RESPONSE SURFACE METHODOLOGY AND ARTIFICIAL NEURAL NETWORKS

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Abstract

Artificial neural networks are a powerful tool for modeling of extrusion processing of food materials. Wheat flour and wheat– black soybean blend (95:5) were extruded in a single screw Brabender extruder with varying temperature (120 and 140 °C), dry basis moisture content (18 and 20%) and screw speed (156, 168, 180, 192 and 204 rpm). The specific mechanical energy, water absorption index, water solubility index, expansion ratio and sensory characteristics (crispness, hardness, appearance and overall acceptability) were measured. Well expanded products could be obtained from wheat flour as well as the blend of wheat– black soybean. The results showed that artificial neural network (ANN) models performed better than the response surface methodology (RSM) models in describing the extrusion process and characteristics of the extruded product in terms of specific mechanical energy requirement, expansion ratio, water absorption index, water solubility index as well the sensory characteristics. The ANN models were better than RSM models both in case of the individual as well as the pooled data of wheat flour and wheat- black soybean extrusion.

Keywords: Extrusion, Modeling, Artificial Neural Networks, Response Surface Methodology.

Nomenclatures

m	Moisture content, % dry basis
n	Number of data points
S	Screw speed [rpm]
T	Barrel temperature [°C]
ER	Expansion Ratio
r^2	Regression coefficient
R_A	Sensory rating based on appearance
R_C	Sensory rating based on crispness
R_H	Sensory rating based on hardness
R_O	Sensory rating based on overall acceptability
RE	Relative Error, %
SME	Specific Mechanical Energy
WAI	Water Absorption Index
WSI	Water Solubility Index
X_i, X_j 's	Independent variables
Y	Response variable
Y_p	Predicted value
Y_a	Actual value
<i>Greek Symbols</i>	
β_i, β_{ij} 's	Coefficients of response surface models

1. Introduction

High temperature short time (HTST) extrusion cooking technology has limitless applications in processing of cereal based products. Extrusion cooking is a popular means of preparing snacks and ready to eat foods. It is a versatile and efficient method of converting raw materials into finished food products. Its advantages include energy efficient, lack of process effluents and versatility with respect to ingredient selection, and the shapes and textures of products that can be produced. Extrusion processing is used for processing of starch as well as proteinacious material. Therefore, it is believed to be an important food processing technique for preparation of nutritious food.

Modeling of extrusion processing involves consideration of process parameters, system parameters, and product properties [1]. Thus, extrusion cooking modeling is a multiple input and multiple output process. Though mathematical modeling of food extrusion process has benefited from available information on plastic extrusion, modeling of quality changes during food extrusion is a difficult task. Because of large number of process variables involved and nonlinear relationship among them, several

approximations have to be made, which limit the result of mathematical models [2]. Many of the research efforts on understanding the transformation in extruder have been empirical. The response surface methodology (RSM) has been widely used approach for modeling of extrusion processing [3-5]. It is a collection of mathematical and statistical techniques useful for analyzing and optimizing the response of multivariate system.

In addition, artificial neural networks (ANN) are being used in the field of food processing due to their ability for solving non-linear problems [6-9]. Neural networks are useful when exact mathematical information is not available. Another advantage of a neural network model over a rule based model is that, if the process under analysis changes, new data can be added and the neural network can be trained again. This is much easier than determining new models or rules.

Artificial neural networks are mathematical models of biological neural systems. It learns from examples through iteration, without requiring a priori knowledge of relationships between variables under investigation. Each example includes both inputs (information used to make a decision) and patterns (prediction or responses). ANN tries each example in turn using the inputs to calculate answers which it compares to provided pattern. If it is wrong, ANN corrects the network by making changes to internal connections (weights). The trial and error process continues until the network outputs are in good agreement with patterns to a certain specified level of accuracy.

Ganjyal & Hanna have highlighted the potential of neural networks in the modeling of residence time distribution (RTD) in food extruders. They modeled the data available in literature using NN and found improved predictability compared to the regression models [6]. Popescu and co-workers have presented a NN model leading to an expert system controller for the start up part of corn extrusion [8]. However the comparative performance of ANN and RSM models in describing the extrusion process need to be evaluated. Therefore, this study was undertaken to model the extrusion processing of wheat flour and wheat – black soybean blend using RSM and ANN models and compare them.

2. Materials & Methods

2.1 Experimental Data on Extrusion Process and Extrudate Characteristics

Wheat flour and black soybean grains available commercially were procured from local market. Black soybean grains were cleaned using Carter Day dockage tester and dehusked in a dhal mill. Dehusked grains were milled to fine flour. Dry basis moisture content of both materials was adjusted to 18% and 20% separately using two stage conditioning. Conditioned wheat flour and black soybean flour were mixed in proportion of 95:5 for blend product. Salt (1.5%) was added for taste. Blended samples were stored at 5°C for 12 h in polythene bags. The polythene bags were

shaken intermittently to ensure proper mixing and moisture equalization. Samples were allowed to come to room temperature prior to extrusion.

Single screw Brabender laboratory extruder with D0-CORDER 'E' attachment (DCE 330) was used for extruding the product. The length to diameter (L/D) ratio of the extruder was 20:1. Based on literature and trial runs the compression ratio (5:1), temperature of feed section (90°C) and diameter of die (3 mm) were kept constant while barrel temperature (120 and 140°C), dry basis moisture content (18% and 20%), screw speed (156, 168, 180, 192, and 204 rpm) and proportion of wheat flour (100 and 95%) were varied and full factorial design was used for experimentation.

Expansion ratio (ER) was determined by measuring extrudate diameter and die diameter. Water absorption index (WAI) and water solubility index (WSI) were determined by the standard methods. The specific mechanical energy (SME) was measured as net mechanical energy input per unit mass feed rate [10]. The extruded products were also evaluated for their sensory attributes viz. crispness, hardness, appearance and overall acceptability using 9-point hedonic scale.

2.2 RSM and ANN Modeling

Functional relationships between the independent variables (temperature, moisture content and screw speed) and dependent variables (SME, WAI, WSI, ER and sensory scores) were determined using multiple regression technique by fitting second order equation of the form:

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

where β_0 , β_i , β_{ij} and β_{ii} are coefficients, X_i , X_j are independent variables and Y-response (dependant variable) and n is number of independent variables.

In ANN modeling, MATLAB software was used for training and validating of neural network models. Multiple input and multiple output (MIMO) network models were developed for objective parameters and for sensory attributes. Standard Bayesian regularization back propagation training algorithm, **trainbr** function, was used for training the network. This training function updates the weight and bias values according to Levenberg – Marquardt algorithm. It is one of the best ways to improve generalization performance of network for function approximation problems. This is because it does not require that a validation data set be separated out of the training data set. It uses all of the data. This advantage is especially noticeable when the size of data set is small. It minimizes a linear combination of squared errors and weights and then determines the correct combination to produce network that generalizes well [11]. The number of neurons in hidden layer was determined by trial and error

procedure. The optimum configuration was decided based on minimizing the difference between neural network prediction and desired output less than 10^{-3} .

To get optimum configuration of neural network, the number of learning runs were fixed at 20,000 which were sufficient and the number of neurons in hidden layer was varied from 8 to 16. The modeling performance was evaluated by statistical parameters average relative error, RE and regression coefficient, r^2 [12]. Mathematically, they were as follows:

$$RE = \frac{\sum_{j=1}^n |Y_{a_j} - Y_{p_j}| / n}{Y_{a_{max}} - Y_{a_{min}}} \quad (2)$$

and

$$r^2 = \left(1 - \frac{\sum_{j=1}^n (Y_{p_j} - Y_{a_j})^2}{\sum_{j=1}^n (Y_{p_j} - Y_{a_{mean}})^2} \right) \quad (3)$$

3. Results & Discussion

In the extrusion experiments, the Specific mechanical energy (SME) ranged from 168.12 - 246.65 kJ/kg for wheat flour product and from 139.42 to 203.76 kJ/kg for blend. WAI, WSI and ER ranged between 5.56-8.14, 9.98-14.6 and 2.73-3.55 for wheat flour while they were 4.01-7.85, 5.57-11.12 and 2.67-3.45 for blend, respectively. Crispness, hardness, appearance and overall acceptability were in the range 5.9-7.8, 5.1-7.1, 6.2-7.5 and 6.0-7.6, respectively for wheat flour extrudate. Correspondingly, they were 5.6-7.5, 5.2-6.5, 5.5-7.4 and 5.6-7.2 for blend.

3.1 RSM Modeling

Second order model fitted to response data of individual wheat flour and blend products was good descriptor for process parameters than those of pooled data. Square term was non-significant. The following models were obtained for wheat and blend:

Wheat

$$SME = -2470.8 + 18.892 T + 134.73 m + 2.19 S - 0.9996 m.T - 0.00009 T.S - 0.0753 m.S \quad (r^2 = 0.897)$$

$$\begin{aligned}
 ER &= 0.446 - 0.0254 T + 0.4768 m + 0.0135 S - 0.0015 m.T \\
 &\quad + 0.0002 T.S - 0.0025 m.S \quad (r^2 = 0.891) \\
 WSI &= 6.94 + 0.2861 T + 1.362 m - 0.206 S - 0.026 m.T \\
 &\quad + 0.001 T.S + 0.007 m.S \quad (r^2 = 0.787) \\
 WAI &= 84.65 - 0.532 T - 2.393 m - 0.214 S + 0.0144 m.T \\
 &\quad + 0.0012 T.S + 0.0033 m.S \quad (r^2 = 0.625) \\
 R_A &= - 48.76 + 0.539 T + 1.419 m + 0.08 S - 0.017 m.T \\
 &\quad - 0.001 T.S + 0.003 m.S \quad (r^2 = 0.559) \\
 R_H &= - 14.58 + 0.457 T + 0.59 m - 0.135 S - 0.020 m.T \\
 &\quad - 0.001 T.S + 0.010 m.S \quad (r^2 = 0.745) \\
 R_C &= - 26.16 + 0.565 T + 1.6 m - 0.183 S - 0.028 m.T \\
 &\quad - 0.0001 T.S + 0.0100 m.S \quad (r^2 = 0.734) \\
 R_O &= -45.2 + 0.562 T + 2.21 m - 0.04 S - 0.026 m.T - 0.001 T.S \\
 &\quad + 0.005 m.S \quad (r^2 = 0.667)
 \end{aligned}$$

Blend

$$\begin{aligned}
 SME &= 1983.6 - 13.373 T - 94.53 m - 1.163 S + 0.6605 m.T \\
 &\quad + 0.0092 T.S + 0.0263 m.S \quad (r^2 = 0.866) \\
 ER &= 38.523 - 0.3046 T - 2.094 m + 0.0443 S + 0.0173 m.T \\
 &\quad - 0.0001 T.S - 0.0012 m.S \quad (r^2 = 0.914) \\
 WSI &= 363.15 - 2.8099 T - 19.296 m + 0.1304 S + 0.1504 m.T \\
 &\quad - 0.0001 T.S - 0.0004 m.S \quad (r^2 = 0.955) \\
 WAI &= 317.98 - 2.3193 T - 13.901 m - 0.2692 S + 0.1024 m.T \\
 &\quad + 0.0019 T.S + 0.0008 m.S \quad (r^2 = 0.916) \\
 R_A &= - 24.35 + 0.0519 T + 1.869 m + 0.1045 S - 0.006 m.T \\
 &\quad - 0.002 T.S - 0.006 m.S \quad (r^2 = 0.536) \\
 R_H &= 29.280 - 0.200 T - 0.120 m - 0.060 S + 0.001 m.T \\
 &\quad + 0.0008 T.S - 0.001 m.S \quad (r^2 = 0.734) \\
 R_C &= 35.02 - 0.23 T - 0.48 m - 0.09 S + 0.003 m.T \\
 &\quad + 0.001 T.S + 0.0021 m.S \quad (r^2 = 0.644) \\
 R_O &= 9.63 - 0.09 T + 0.194 m + 0.021 S + 0.001 m.T + 0.003 \\
 &\quad T.S - 0.002 m.S \quad (r^2 = 0.668)
 \end{aligned}$$

It can be seen that the SME model accounted 89.7% and 86.64% variability in the data of wheat flour product and blend product, respectively. WAI accounted only 62.5% variability in the wheat flour data suggesting poor fit while it described adequately in blend product. The model for WSI was inadequate incase of wheat flour product since it accounted 78.7% variability in the data. For blend product it predicted WSI adequately.

Regression analysis for sensory characteristics shows that the RSM models did not describe the responses very well, probably due to the subjective nature of the data.

3.2 ANN Modeling

A complete set of data as well as data for individual product was analyzed by employing artificial neural network technique using MATLAB software for objective and sensory characteristics. MIMO prediction model was developed using MATLAB. Inputs were composition (proportion of wheat flour), temperature, moisture content, and screw speed while outputs were SME, WAI, WSI, and ER for objective parameters and crispness, hardness, appearance and overall acceptability for sensory evaluation.

The performance of ANN models for all responses during training and testing is summarized in Table 1. The high coefficient of determination ($r^2 > 0.9$) and low relative error ($RE < 3.6\%$) indicated that the ANN model described the input-output relationship for SME, WAI, WSI, ER and sensory responses in complete data set very well. A three layer feed forward network (3-8-4) consisting one input layer one output layer and one hidden layer satisfactorily described the experimental data on SME, ER, WAI and WSI in case of wheat flour and wheat-black soybean blend. A slightly larger three layer feed forward network (4-14-4) was required for the pooled data of both the feed materials. The correlation coefficients for generalization (testing) were quite similar or higher than those for training. For individual product data set, prediction of objective responses was good ($r^2 > 0.9$) while it was unsatisfactory for subjective measurements. Fig. 1 shows the simulated and experimental data for SME, ER, WAI and WSI. It can be seen that the ANN models very well matched the experimental data.

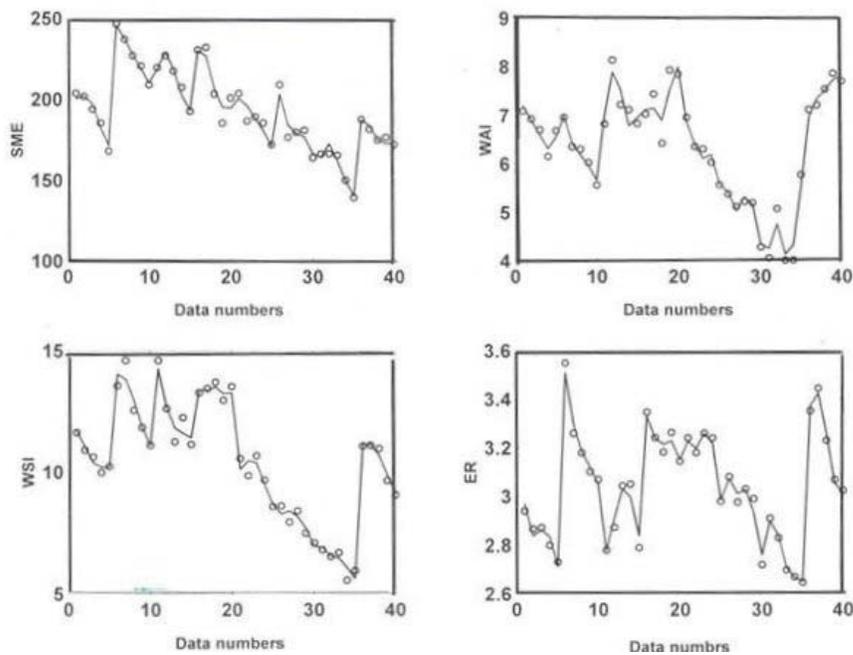


Fig. 1. Comparison between simulated (-) and actual (o) objective responses

A four layer feed forward network (3-8-6-4) consisting one input layer, one output layer and two hidden layers, satisfactorily described the experimental data on the sensory characteristics of extruded products made from wheat flour and wheat–black soybean blend. A slightly larger four layer feed forward network (4-8-8-4) was required the pooled data of both the feed materials. Fig. 2 shows the comparison between the simulated and experimental data for sensory characteristics. In case of sensory characteristics also very good predictions was obtained.

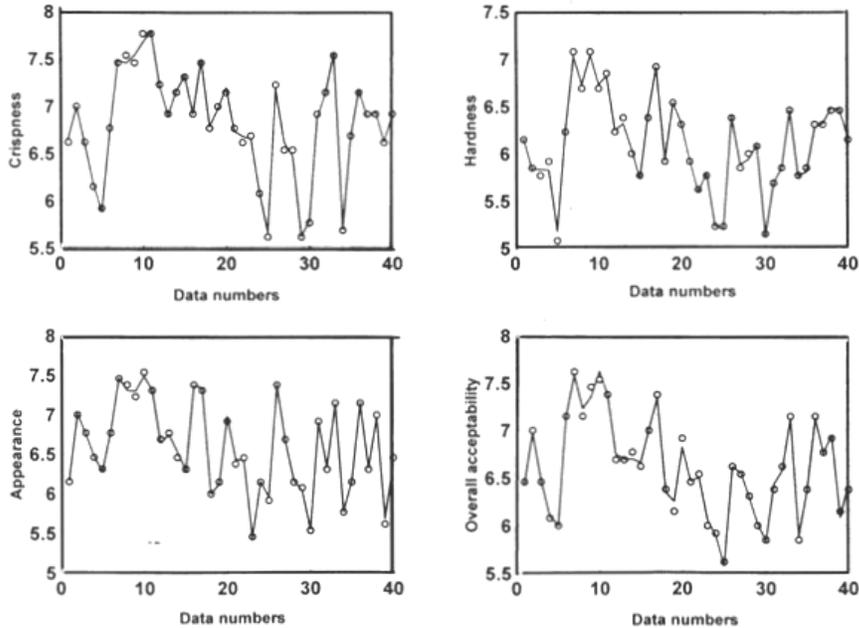


Fig. 2 Comparison between simulated (-) and actual (o) sensory attributes.

3.3 Comparison between ANN and RSM models

The prediction performance of RSM and ANN models in terms of coefficient of determination is also shown in Table 1. It shows that in all the cases, the ANN models had better prediction than RSM models.

4. Conclusions

Artificial neural networks are a powerful tool for modeling of extrusion processing of food materials. Well expanded products could be obtained from wheat flour as well as the blend of wheat–black soybean. ANN models performed better than the RSM models in describing the extrusion process and characteristics of the extruded product in terms of specific mechanical energy requirement, expansion ratio, water absorption index, water solubility index as well the sensory characteristics.

Table 1. Comparison of RSM and ANN models for training and testing of various extrusion parameters

Modeled response	Training/ Testing	Wheat Flour				Blend Flour				Pooled data set			
		ANN		RSM		ANN		RSM		ANN		RSM	
		MSE	RE %	r ²	r ²	MSE	RE %	r ²	r ²	MSE	RE %	r ²	r ²
SME	Train	0.179	1.6	0.994	0.897	0.636	5.32	0.9	0.866	0.451	2.6	0.975	
	Test	0.1	1.73	0.99	0.139	0.139	2.4	0.93	0.199	2.32	0.978		
WAI	Train	0.107	1.02	0.997	0.625	0.645	5.68	0.949	0.916	0.57	3.6	0.97	
	Test	0.061	1.16	0.998	0.355	0.355	4.57	0.924	0.267	3.89	0.974		
WSI	Train	0.09	0.82	0.998	0.787	0.442	3.95	0.976	0.955	0.443	2.7	0.982	
	Test	0.052	0.8	0.998	0.122	0.122	2.28	0.99	0.143	1.82	0.992		
ER	Train	0.157	1.39	0.991	0.891	0.449	4.2	0.969	0.914	0.356	2.27	0.986	
	Test	0.052	0.9	0.998	0.227	0.227	3.98	0.957	0.137	1.76	0.994		
Rc	Train	0.071	12.01	0.646	0.734	1.528	12.1	0.645	0.644	0.229	2.9	0.995	
	Test	0.038	7.57	0.769	0.467	0.467	7.61	0.796	0.116	2.76	0.993		
RH	Train	0.13	13.04	0.715	0.745	1.463	13.04	0.715	0.734	0.229	2.75	0.995	
	Test	0.085	7.06	0.874	0.394	0.394	7.05	0.904	0.129	3.13	0.988		
RA	Train	0.14	16.92	0.497	0.559	1.801	16.89	0.495	0.536	0.222	2.76	0.996	
	Test	0.076	12.36	0.586	0.588	0.588	12.16	0.564	0.132	0.99	0.991		
Ro	Train	0.126	10.88	0.666	0.667	1.413	10.87	0.666	0.668	0.289	3.55	0.992	
	Test	0.067	4.89	0.912	0.34	0.34	4.77	0.922	0.159	4.19	0.985		

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