Modeling Selected Properties of Extruded Rice Flour and Rice Starch by Neural Networks and Statistics[1]

G. Ganjyal,[2,3] M. A. Hanna,[3–5] P. Supprung,[6] A. Noomhorm,[6] and D. Jones[5]

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ABSTRACT

Rice flour and rice starch were single-screw extruded and selected product properties were determined. Neural network (NN) models were developed for prediction of individual product properties, which performed better than the regression models. Multiple input and multiple output (MIMO) models were developed to simultaneously predict five product properties or three product properties from three input parameters; they were extremely efficient in predictions with values of $R^2 > 0.95$. All models were feedforward backpropagation NN with three-layered networks with logistic activation function for the hidden layer and the output layers. Also, model parameters were very similar except for the number of neurons in the hidden layer. MIMO models for predicting product properties from three input parameters had the same architecture and parameters for both rice starch and rice flour.

Food extrusion process modeling has been a difficult task due to its complexities. Various research efforts intended to model the process have been more machine- and product-specific. The whole process can be viewed as consisting of a set of input parameters such as raw material characteristics, moisture content, feed rate, screw speed, screw configuration, and barrel temperature; system parameters such as residence time, specific mechanical energy, and pressure build up; and product properties such as radial expansion, mechanical properties, and chemical properties. These parameters are interdependent. Many researchers have tried to relate input parameters and output parameters, mainly using regression models to fit the experimental data. Some research efforts have concentrated on using regression analysis to predict system parameters from input parameters.

Two approaches have been followed in modeling extrusion operations: dynamic modeling and steady state modeling. Dynamic modeling (Levine et al 1986, 1987) describes the reaction of a process immediately after a perturbation (10–15 sec) and is particularly useful for control and automation, while steady state modeling describes the state of the process after a period long enough for machine stabilization. Between dynamic and steady state models lies the domain of long period (a few minutes) instabilities and metastable states (Roberts and Guy 1986, 1987) that probably can be explained by qualitative models.

Most studies directed toward understanding transformations in extruders have been empirical in nature. The most widely used approach is response surface methodology. This approach allows one to establish mathematical relationships between input variables and product properties (Olkku and Vainionpaa 1980; Antila et al 1983; Frazier et al 1983; Olkku et al 1984; Fletcher et al 1985). These results are clearly product- and machine-specific, and the conclusions are limited to the scope of the investigations.

Other approaches have been proposed. Mueser et al (1987) and Mueser and Van Langerich (1984) proposed a system analytical model for extrusion cooking of starch. Their model distinguished between process and system parameters that influenced target product properties (output parameters). Process parameters are the operating conditions that can be controlled and manipulated directly. System parameters are the properties that are influenced by the process parameters and subsequently affect the product characteristics (target parameters). It is believed that there is an appropriate function to describe the relationship between process parameters and system parameters or between system parameters and target parameters. This approach allows one to compare results obtained on the basis of more meaningful independent variables by eliminating the effects of operating conditions, materials processed, and extruder layout and geometry. In addition, the information is particularly useful for the scale-up of extrusion processes. Building on that model, many researchers have studied the relationships between process and target parameters (Taranto et al 1975; Olkku and Vainionpaa 1980; Antila et al 1983; Frazier et al 1983; Launay and Lisch 1984; Olkku et al 1984; Owusu-Ansah et al 1984; Fletcher et al 1985; Bhattacharya and Hanna 1987; Chinnaswamy and Hanna 1988). Only a limited number of studies have been reported on modeling system parameters from process parameters (Yacu 1985; Tayeb et al 1988) or building correlations between system parameters and target parameters (Guy and Horne 1988; Kirby et al 1988; Mueser et al 1987).

Though regression techniques are commonly used, difficulties arise when dealing with the complex characteristics of some systems. Regression is usually limited to linear and static systems, and conventional nonlinear regression algorithms are clumsy when handling systems like the extrusion process with multiple inputs and outputs. One limitation to traditional mathematical modeling is that the mathematical relationships describing each process of the system must be closely approximated to obtain good results. Limitations in information introduce error in model predictions. Alternative techniques such as neural networks (NN) can reduce this difficulty (Batchelor et al 1997).

For nonlinear problems, NN are a promising alternative technique (Borggard and Thodberg 1992). NN learn from examples through iteration, without requiring a priori knowledge of relationships between variables under investigation (Linko et al 1992; Erikaineen et al 1994). The advantage of NN over a rule-based model is that, if the process under analysis changes, new examples can be added and the NN can be retrained. This is easier than determining new models or rules. Moreover, no statistical assumptions are made on the behavior of the data. NN are not known for precision; if precision is less important than speed, NN may be useful. NN models have performed well even with noisy, incomplete, or inconsistent data (Bochereau et al 1991). Linko et al (1992) used NN with output feedback and time delays for the

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[2] MGP Ingredients, Inc., Atchison, KS 66002.

[3] University of Nebraska, Industrial Agricultural Products Center, 208 L.W. Chase Hall, Lincoln, NE 68583-0730.

[4] Corresponding author. Phone: 1-402-472-1634. Fax: 1-402-472-6338. E-mail: mhanna1@unl.edu

[5] University of Nebraska, Biological Systems Engineering Department, 215 L.W. Chase Hall, Lincoln, NE 68583-0730.

[6] Asian Institute of Technology, Food Engineering and Bioprocess Technology, P.O. Box 4, Pathumthani, Thailand 12120.

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control of specific mechanical energy on the basis of screw speed for flat bread production through a twin-screw extrusion cooker. As a food extruder is a multiple input and multiple output (MIMO) system, dynamic changes in torque, specific mechanical energy, and pressure were modeled and subsequently controlled using two independently trained feedforward artificial NN (Eerikainen et al 1994). Linko (1998) presented a review on the potential of some novel tools in food process control. NN have great potential as software sensors for online, real-time state estimation, and prediction in complex process control applications.

Taking into consideration the current status of extrusion modeling, the objective of this research was to model the extrusion of rice flour and rice starch with NN. The specific objectives were to develop more robust NN models for prediction of selected product properties from the input process variables individually for each property and to develop multiple input and multiple output models for simultaneous prediction of all product properties.

MATERIALS AND METHODS

Rice flour and rice starch were extruded at three levels of moisture content, screw speed, and barrel temperature. Broken kernels of KDML 105 rice, as a by-product from the milling process, were obtained from the Siam Grain Company, Bangkok, Thailand. Rice flour was prepared by a wet-milling method and rice starch was prepared by an alkaline method (Hogan 1967).

Extrusions

Extrusions were conducted in a single-screw laboratory cooking extruder (19 mm screw diameter; L/D ratio 20:1) (C.W. Brabender Instruments, NJ). Uniformly tapered screws with nominal compression ratio of 4:1 were used. The zone 3 (die section) barrel temperature was adjusted to the desired temperatures of 140, 170, and 200°C, whereas zone 1 (the feed section) of the barrel was fixed at 125°C and zone 2 was fixed at 135°C. Screw speeds were 150, 200, and 250 rpm with fixed feed rate of 40 g/min. The moisture contents of the samples used were 18 ± 2.0, 23 ± 2.0, and 28 ± 2.0% (wb). There were two replicates of each test run. It was a complete randomized design with a full factorial arrangement of treatments.

Desired moisture level was achieved by spraying distilled water as a fine mist onto the samples. Samples were then tempered for 20 min in a blender and moisture content was determined at this point. These samples were sealed in plastic bags and refrigerated at 4°C for one day. Before extrusion, the samples were brought to about room temperature and mixed to assure even moisture distribution. Each extrusion run was brought to steady state as indicated by constant torque and melt temperatures before sampling and data collection. The extrudates collected were cooled at room temperature for 2 hr and sealed in plastic bags for analyses (Martinez et al 1988).

Analytical Methods

Moisture contents of rice flour and rice starch were analyzed by AOAC methods (1984). Mean values were obtained from three measurements. Expansion ratio (ER) was measured as the ratio of cross-sectional area of extrudate to that of the die nozzle (Bhattacharya and Choudhury 1994). Mean expansion ratio of each sample was determined from 10 observations.

Modified procedures of Anderson et al (1969) were used to determine water absorption index (WAI) and water solubility index (WSI) of extrudates. For determination of WAI, 0.5 g of extruded and ground sample (100 mesh) were suspended in 15 mL of distilled water at 25°C with constant stirring for 30 min and then centrifuged at 3,000 rpm for 10 min. Supernatant liquid was poured into a tarred evaporating dish and dried at 100 ± 5°C for 4 hr. Weight of the remaining gel was taken as WAI and expressed as g/g of dry sample. Amount of dried solids recovered by evaporating the supernatant was taken as WSI and expressed as percentage of dry solids. Experiments were performed in triplicate.

Degree of gelatinization (DG) is defined as the weight ratio of gelatinized flour or starch to total weight of dry sample. DG was determined using the method of Birch and Priestley (1973), which is based on formation of a blue iodine complex by amylose released during gelatinization. Percentage DG was calculated by the absorbance ratio of amylose-iodine complex for samples dispersed in 0.060*M* KOH compared with respective samples dispersed in 0.4*M* KOH. Reported results were averages of three replicate analyses.

Initial peak viscosity (IPV) of extrudate samples was measured using a Rapid Visco Analyser (Series 4, RVA Newport Scientific Pty. Ltd., Australia) at 25°C just before heating. Measurement was based on the method of Guha et al (1998). Apparent viscosity and temperature profiles were recorded and monitored with a PC. Curves were analyzed for IPV. Three measurements were made on each sample and IPV was reported in rapid visco units (RVU).

Statistical Analysis

Multiple regression models (SPSS/PC v. 6) were used to analyze data. All possible procedures for variable reduction were used to determine the predictors for regression models (Neter et al 1990). Criteria for selection of a model were 1) the number of variables should be close to the number of parameters in the model, 2) R^2 should be close to 1, and 3) SE should be low.

TABLE I
Neural Network (NN) Models for Each Product Property for Rice Flour Extrusion[a,b]

Output	ER	WAI	WSI	DG	IPV
R^2	0.9565	0.9677	0.9146	0.9381	0.9831
SE	0.0775	0.1265	1.6229	0.8114	1.0884
Network	3 20 1	3 15 1	3 20 1	3 25 1	3 18 1

[a] SE, standard error; ER, expansion ratio; WAI, water absorption index; WSI, water solubility index; DG, degree of gelatinization; IPV, initial peak viscosity.
[b] LR, learning rate = 0.3; MO, momentum = 0.2; IW, initial weight = 0.3.

TABLE II
Neural Network (NN) Model for Prediction of All Five Product Properties (MIMO model) for Rice Flour Extrusion[a,b]

Output	ER	WAI	WSI	DG	IPV
R^2	0.9547	0.9459	0.9193	0.9191	0.9392
SE	0.0894	0.1643	1.6577	2.4048	3.3211
Network	3 15 5				

[a] MIMO, multiple input and multiple output; SE, standard error; ER, expansion ratio; WAI, water absorption index; WSI, water solubility index; DG, degree of gelatinization; IPV, initial peak viscosity.
[b] LR, learning rate = 0.3; MO, momentum = 0.2; IW, initial weight = 0.3.

Neural Network Modeling

NN modeling was performed using commercial software (NeuroShell 2, Ward Systems Group, Frederick, MD). A typical single layered neural network is shown in Fig. 1. The criteria used for the NN model evaluation were the R^2 and standard error (SE). Data sets were divided randomly, 70% as training and 30% as testing sets. Three-layered feedforward networks were used with a backpropagation algorithm. The networks were trained rigorously varying the number of neurons in the hidden layer, learning rates, momentum, and initial weights to arrive at optimum values of all the parameters when the error was lowest. The best networks were saved.

RESULTS AND DISCUSSION

NN models were developed to predict individual product properties from the three input parameters. The models developed for individual product properties for both rice flour and rice starch are shown in Tables I and IV. The corresponding regression models are shown in Table VII. The NN models had almost the same architecture, with the only variation being in the number of neurons in the hidden layer. All the models performed well with the testing data with R^2 values of greater than 0.91 and a majority of them greater than 0.95. The regression models also performed well, with R^2 values greater than 0.88. The variables and their combinations were very different for the regression models. NN models had higher R^2 values and lower standard error values of prediction than did the regression models.

MIMO models were developed for the prediction of all product properties at one time from the input parameters. The NN models for rice flour and rice starch are shown in Tables II through V. Again it was found that the architecture of the models were very similar except for the number of neurons in the hidden layer. Another set of MIMO models was developed to predict three of the product properties (ER, WAI, and WSI, as these three properties would be sufficient to explain the product characteristics) from the input parameters. Interestingly, the models developed for both rice flour and rice starch were similar (Tables III and VI, respectively). So, it was possible to develop a general model for prediction of ER, WAI, and WSI for both rice flour and rice starch. It is not possible to handle the MIMO systems by regression. Thus, NN proved to be more powerful in modeling the extrusion of rice flour and starch.

CONCLUSIONS

Neural networks models, developed to predict expansion ratios, water absorption index, and water solubility index individually from moisture content, screw speed, and barrel temperature were better than regression models. The NN models developed for different raw materials were very much similar in their prediction

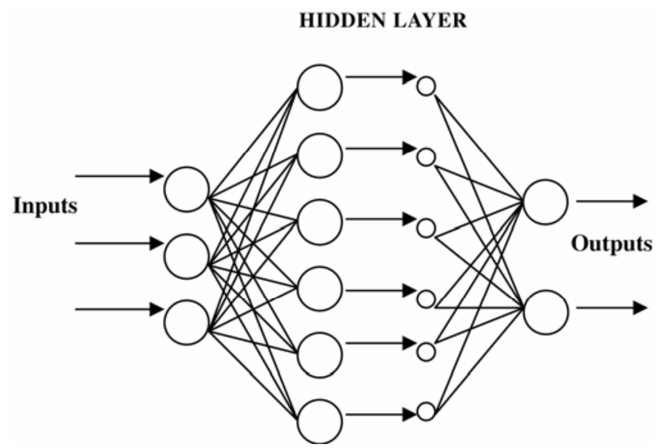

Fig. 1. Typical single-layered neural network (Ganjyal and Hanna 2001).

TABLE III
Neural Network (NN) Model for Prediction of Three Product Properties (MIMO model) for Rice Flour Extrusion[a,b]

Output	ER	WAI	WSI
R^2	0.9491	0.9490	0.9128
SE	0.0837	0.1643	1.7044
Network	3 15 3		

[a] MIMO, multiple input and multiple output; SE, standard error; ER, expansion ratio; WAI, water absorption index; WSI, water solubility index.
[b] LR, learning rate = 0.3; MO, momentum = 0.2; IW, initial weight = 0.3.

TABLE VI
Neural Network (NN) Model for Prediction of Three Product Properties (MIMO model) for Rice Starch Extrusion[a,b]

Output	ER	WAI	WSI
R^2	0.9547	0.9747	0.9712
SE	0.0837	0.1048	0.7396
Network	3 15 3		

[a] MIMO, multiple input and multiple output; SE, standard error; ER, expansion ratio; WAI, water absorption index; WSI, water solubility index.
[b] LR, learning rate = 0.3; MO, momentum = 0.2; IW, initial weight = 0.3.

TABLE IV
Neural Network (NN) Models for Each Product Property for Rice Starch Extrusion[a,b]

Output	ER	DG	WAI	WSI	IPV
R^2	0.9595	0.9583	0.9687	0.9491	0.9863
SE	0.0775	1.7942	0.1183	0.9445	1.6084
Network	3 5 1	3 7 1	3 12 1	3 20 1	3 25 1

[a] SE, standard error; ER, expansion ratio; DG, degree of gelatinization; WAI, water absorption index; WSI, water solubility index; IPV, initial peak viscosity.
[b] LR, learning rate = 0.3; MO, momentum = 0.2; IW, initial weight = 0.3.

TABLE V
Neural Network (NN) Model for Prediction of All Five Product Properties (MIMO model) for Rice Starch Extrusion[a,b]

Output	ER	DG	WAI	WSI	IPV
R^2	0.9455	0.9468	0.9622	0.9568	0.9807
SE	0.0894	2.0445	0.1304	0.8741	1.8300
Network	3 10 5				

[a] MIMO, multiple input and multiple output; SE, standard error; ER, expansion ratio; DG, degree of gelatinization; WAI, water absorption index; WSI, water solubility index; IPV, initial peak viscosity.
[b] LR, learning rate = 0.3; MO, momentum = 0.2; IW, initial weight = 0.3.

TABLE VII
Regression Models for Product Properties Using Feed Moisture Content (M), Screw Speed (S) and Barrel Temperature (T) as Independent Variables[a]

Property	Regression Models	R^2	SE
Rice flour			
ER	$1.5275 - 0.0069 * M^2 - 0.0054 * T + 0.2156 * M$	0.94	0.09
WAI	$2.2161 + 0.336 * M + 0.00003 * ST - 0.00042 * MS - 0.0005 * MT$	0.94	0.19
WSI	$80.2255 - 2.4321 * M + 0.0015 * MS + 0.0050 * MT - 0.0902 * T$	0.90	1.79
DG	$-261.3802 + 14.1016 * M - 0.3118 * M^2 + 0.0019S * T - 0.000075 * MST + 0.0216 * MT - 0.0058 * T^2 + 1.52 * T$	0.88	3.15
IPV	$-17.7464 + 3.6469 * M - 0.00024 * ST - 0.0017 * MT$	0.95	3.09
Rice starch			
ER	$4.4532 - 0.0924 * M - 0.00006 * T^2$	0.94	0.10
WAI	$8.7234 + 0.0119 * M^2 - 0.000003 * MST - 0.2835 * M + 0.00013 * MS + 0.00042ST$	0.95	0.16
WSI	$47.899 - 0.0724 * M^2 + 0.0128 * MT - 0.0007 * T^2 + 0.00047 * MS$	0.91	1.31
DG	$-399.3925 + 15.268 * M - 0.2648 * M^2 + 1.1148 * S - 0.0021 * S^2 - 0.0110 * MS + 0.0026 * MT - 0.0064T^2 + 2.1169 * T$	0.95	2.19
IPV	$-83.6915 + 0.2085 * M^2 - 0.0003 * ST - 6.0115 * M$	0.94	3.29

[a] ER, expansion ratio; WAI, water absorption index; WSI, water solubility index; DG, degree of gelatinization; IPV, initial peak viscosity.

capabilities and with respect to the architecture of the networks (number of hidden layers, number of neurons in the hidden layers, activation functions used for the hidden and output layers, and the learning method used).

Further, efficient multiple input multiple output (MIMO) models were developed. These MIMO models were very much similar for both rice flour and rice starch. MIMO models predicted the product properties of expansion ratio, water solubility index, and water absorption index for both rice flour and rice starch exactly the same. These analyses confirmed the capabilities of NN to model the extruded product properties efficiently.

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