Artificial Neural Network (ANN) modeling to predict the twin-screw extrusion processing variables of soy protein isolate and corn flour blend formulations on the physical properties of extrudates

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Abstract

The objectives of this study were to develop soy protein isolate and corn flour blend cereal-like extrudates and to develop an artificial neural network (ANN) model to predict the physical properties of soy protein isolate and corn flour blend extrudates as a function of soy protein isolate content, moisture content and extrusion temperature. As per the Central Composite Rotatable Design (CCRD), 20 processing conditions were selected with soy protein isolate content (33.2-66.8%), feed moisture content (31.6-48.4%) and extrusion temperature (126-194℃) and extruded products were developed using a twin-screw extruder. The physical properties (expansion ratio, piece density, breaking stress and rehydration ratio) of the extrudates were determined as response variables. An ANN model was developed to predict the physical properties of extrudates as a function of extrusion processing variables. The results indicated that the ANN model could predict the expansion ratio, piece density, rehydration ratio and breaking stress of soy protein isolate and corn flour blend extrudates with an 89-98% accuracy depending on the physical properties. The study also indicated that about 60% soy protein rich extruded cereals and snacks can be produced to replace the carbohydrate cereal and snack products. The ANN model can be used to setup the extrudates production conditions in a commercial scale.

Keywords: Twin-screw extrusion, soy protein and corn flour extrudate, physical properties, artificial neural network (ANN) model, plant protein rich cereals.

1. Introduction

Extrusion-based food products became a multibillion-dollar market in the world since the extrusion cooking process is very effective in incorporating different food ingredients to develop a number of value-added food products (Grasso, 2020). However, extrusion cooking is being mainly used for producing carbohydrate-based products because aisles after aisles of any large food stores are full of carbohydrate rich snack bars, ready-to-eat cereals and crackers etc. Protein malnutrition is a serious issue in developing countries because of lacking protein content in their diets (Navam et al., 2014). While most people in developed countries are not short of protein in their diets, the recent survey indicates that more than half of them want more protein in their diet because of a growing body of knowledge which indicates that consumption of protein above the recommended dietary allowance (RDA) and restriction of carbohydrate is beneficial in maintaining muscle functions and movability, satiety and treatment of many diseases. Key strategies to compete in the marketing space clearly require that new approaches to processing and presenting proteins such as plant-based proteins into shelf-stable, organoleptically attractive, affordable and convenient products while retaining the maximum amounts of nutrients are needed.

The carbohydrate-based corn flour is commonly used for developing different extruded cereal and snacks because of its availability to expand well under low and high moisture extrusion conditions and low cost (de Mesa et al., 2009; Yu et al., 2012, 2013, 2014). The extruded products using only corn flour lack nutritional values and the nutritional value of extrudates can be increased by blending plant proteins with corn flour which can meet the consumers' demand. In this case, soy protein proved its potential for extruded product development because USA Food and Drug Administration (FDA) approved the use of soy protein in food products for many health benefits (de Mesa et al., 2009). Soy protein can lower the bad cholesterol, act as an anticarcinogenic agent and deters obesity, diabetes, digestive tract irritation, and bone and kidney diseases (de Mesa et al., 2009; Yu et al., 2013). Extrusion cooking process provides thermal and shear energy to the food materials undergoing significant physical and chemical changes for producing foods. The combination of thermal and mechanical energies in this process improves digestibility by gelatinizing starch and denaturing protein and enhance polymerising capacity for producing versatile good quality food products (Alam et al., 2016; Harper, 1981; Moraru and Kokini, 2003). The expansion of puffed extrudates is a fundamental property of extrudates which is directly related to degree of cook (Alam et al., 2016; Moraru and Kokini, 2003). The density, breaking stress and rehydration ratio are affected by the product pores formation (Bisharat et al., 2013; Yu et al., 2013). High expansion, high rehydration ratio, low breaking strength and low piece density are the desirable properties of extruded puffed foods which are a measure of consumer acceptability of final products and are dependent on many extrusion processing variables (i.e. temperature, screw speed, feed rate etc.) and ingredients of product formulations (Alam et al., 2016; Bisharat et al., 2013; de Mesa et al., 2009; Moraru and Kokini, 2003; Yu et al., 2013). The determination of optimum extrusion processing conditions and prediction of the physical properties of extrudates from the extrusion processing variables are necessary.

The regression modeling such as response surface methodology (RSM) is commonly used to characterize multiple extrusion input variables (Basilio-Atencio et al., 2020; Kowalski et al., 2018; Yu et al., 2013). The RSM often solves the second order polynomial equation and predict the trends of independent variables on response variables and reaches to an optimal condition (Basilio-Atencio et al., 2020; Mitra et al., 2020; Mitra, et al., 2011; Timalsina et al., 2019; Yu et al., 2013). Although RSM modeling is commonly used to characterize the extrusion processing conditions the impediment still remains in how to use the predictive trends accurately to predict desired products from a correlation of independent variables and response variables (Kowalski et al., 2018). The prediction accuracy of an RSM model may decrease when the complex nonlinear relationship between independent variables and response variables. In this case, an artificial neural network (ANN) model has potentials as an alternative of an RSM prediction model for a very complex nonlinear multivariate modeling (Yu et al., 2019).

Artificial neural network modeling is growing to estimate and predict the food properties and process for a complex nonlinear relationship between independent and response variables (Chen et al., 2007; Funes et al., 2015; Guiné, 2019; Huang et al., 2007; Mitra, et al., 2011; Sisay et al., 2018). An artificial neural network (ANN) is a powerful data modeling tool which is inspired by the human brain functioning systems (Mitra, et al., 2011; Zurada, 1992). In general, an ANN is a multi-layer feedforward neural network where the neurons are arranged in different layers (input layer, hidden layer, and output layer). Feedforward neural network with one or more hidden layers deals with nonlinear and complex correlation between factors and responses (Mitra, et al., 2011). In this process, an ANN is accomplished by a set of known data so that the trained network can later apply that knowledge developed through the learning of hidden relationship between inputs and outputs on new unknow data to predict the outputs from the given new factors/inputs (Funes et al., 2015; Guiné, 2019; Huang et al., 2007; Mitra, et al., 2011; Zurada, 1992). The adequately trained ANN can predict responses from given factors with a higher accuracy compared to conventional classification or regression analysis (Guiné, 2019). In this study, an artificial neural network (ANN) model was developed as a function of extrusion processing variables (soy protein isolate content, feed moisture content and extrusion temperature) and the performance of the ANN model was evaluated to predict the physical properties (expansion ratio, piece density, breaking stress and rehydration ratio) of soy protein isolate and corn flour blend extrudates accurately.

2. Materials and method

2.1. *Materials*

Corn flour containing 76.7% carbohydrate, 10% protein and 1.7% lipid was purchased from the Brar Natural Flour Mills (Winnipeg, MB, Canada) and soy protein isolate (SPI) was purchased from the American Health & Nutrition (Ann Arbor, MI, U.S.A.), which contained protein of over 90%.

2.2. *Experimental design of soy protein isolate and corn flour blend extrusion*

Central composite rotatable design (CCRD) was used to plan the experimental extrusion conditions. The three input variables/factors in the extrusion processing were soy protein isolate (33.2-66.8%, X_1), feed moisture content (31.6-48.4%, X_2) and extrusion temperature (126-194°C, X_3) and the five levels of extrusion processing input variables were chosen from -1.68 to 1.68 (-1.68, -1, 0, 1, 1.68) as coded values. The selection of the extrusion processing input variables and their ranges were taken on the basis of preliminary experiments. The complete extrusion design consists of total 20 experimental points ($n=2^k + 2k + m$, where, n= total experimental points, input variables, k=3 and central point, m=6), which includes 8 factorial points, 6 axial points and 6 replicated center points (Mitra et al., 2020) as shown in Table 1.

2.3. *Soy protein isolate-corn flour blend preparation and extrusion processing*

Soy protein isolate and corn flour were mixed as per the experimental design (CCRD) shown in Table 1. The mixture was blended thoroughly using a Hobart mixer (Hobart Corp, OH, USA) at a medium speed. The total moisture content of the blends was adjusted gradually during blending as per the design (Table 1). The blending was continued up to homogeneous moisture distribution and proper mixing of the ingredients together.
The blended soy protein isolate and corn flour were extruded using a co-rotating twin-screw extruder (DS32-II, Jinan Saixin Food Machinery, Shandong, P. R. China). The diameter of the screw of the extruder barrel was 30 mm. The length to diameter ratio of the extruder was 20:1. The temperature of the first, second and third zones of the extruder barrel were constant as 100, 120 and 140°C, respectively. The temperature of fourth zone of the barrel (extrusion temperature/die temperature) was adjusted as per the CCRD (Table 1). The soy protein and corn flour blends were fed to the extruder through a conical hopper with a constant feed rate (20 Kg/hr) and a constant extruder screw speed (100 rpm) was maintained. The extrudates came through a 3.8 mm die and cut into about 25 mm long cylindrical pieces. The cut extrudates were then dried at 80°C for 2 hours with a hot-air dryer to reach to a moisture content about 8-10%. The dried extrudates were cooled to a room temperature (20°C), packed in plastic containers and stored at room temperature for further analysis.

2.4. *Determination of physical properties of soy protein isolate-corn flour blend extrudates*

The expansion ratio, piece density (g/mL), breaking stress (MPa) and rehydration ratio of extrudates were determined. The expansion ratio of extrudates is defined as the ratio of the diameter of the extrudate to the diameter of the die (Yu et al., 2013). The diameter of 20 randomly selected extrudates for each sample were measured using a digital calliper and the average expansion ratio of each sample was determined. The piece density of the extrudates were determined using the rapeseed displacement method (AACC, 2001; Mitra et al., 2019). Two replications were conducted and the average value of the piece density (g/mL) of extrudates were reported. The breaking stress of the extrudates was measured using a Lloyd texture machine with a 500 N load cell (Lloyd model LRX, Lloyd Instruments Ltd., Fareham, Han, UK). A three-point breaking test was used to measure the maximum force required to break the extrudate samples. The extrudate was cut to obtain 25 mm-long strands, which were placed at right angle on two rounded stands (bridge) 20 mm apart. The rounded crosshead exerting force in the middle of the bridge was moving down at 1mm/s until breaking. Breaking stress (MPa) was determined as the breaking force per unit cross sectional area. 15 measurements were conducted for each sample and the average breaking stress of extrudates was reported. In order to determine the rehydration ratio of extrudates about twenty-five grams of extrudates were submerged in 500 mL of water at 20°C for 20 min. The rehydrated samples were

Table 1. Experimental design (CCRD) of extrusion processing and the results of physical properties of soy protein isolate and corn flour blend extrudates

Run	Soy protein content, S (%)	Moisture content, M (%)	Temperature, T (°C)	Expansion ratio	Piece density (g/mL)	Breaking stress (MPa)	Rehydration ratio
	X1	X2	X3				
1	1 (60)	1 (45)	1 (180)	1.51±0.08	0.514±0.05	0.823±0.65	0.959±0.07
2	1 (60)	1 (45)	-1 (140)	1.45±0.13	0.723±0.04	0.141±0.01	0.949±0.05
3	1 (60)	-1 (35)	1 (180)	1.69±0.12	0.423±0.01	0.458±0.02	1.410±0.08
4	1 (60)	-1 (35)	-1 (140)	1.43±0.12	0.664±0.03	0.246±0.02	1.150±0.11
5	-1 (40)	1 (45)	1 (180)	1.28±0.08	0.656±0.05	0.332±0.02	1.550±0.08
6	-1 (40)	1 (45)	-1 (140)	1.35±0.07	0.528±0.04	0.179±0.01	0.488±0.03
7	-1 (40)	-1 (35)	1 (180)	1.37±0.11	0.613±0.03	0.523±0.02	1.570±0.09
8	-1 (40)	-1 (35)	-1 (140)	1.31±0.08	0.771±0.05	0.541±0.02	0.583±0.03
9	1.68 (66.8)	0 (40)	0 (160)	1.39±0.07	0.741±0.03	0.282±0.02	0.818±0.06
10	-1.68 (33.2)	0 (40)	0 (160)	1.41±0.07	0.462±0.02	0.431±0.03	1.320±0.03
11	0 (50)	1.68 (48.4)	0 (160)	1.49±0.08	0.541±0.02	0.196±0.01	0.962±0.05
12	0 (50)	-1.68 (31.6)	0 (160)	1.45±0.12	0.669±0.03	0.586±0.02	1.260±0.06
13	0 (50)	0 (40)	1.68 (194)	1.51±0.09	0.452±0.02	0.726±0.02	1.950±0.04
14	0 (50)	0 (40)	-1.68 (126)	1.35±0.07	0.791±0.02	0.237±0.02	0.603±0.03
15	0 (50)	0 (40)	0 (160)	1.74±0.07	0.475±0.02	0.784±0.05	1.380±0.06
16	0 (50)	0 (40)	0 (160)	1.73±0.14	0.478±0.03	0.716±0.04	1.390±0.04
17	0 (50)	0 (40)	0 (160)	1.77±.0.11	0.466±0.04	0.771±0.04	1.430±0.11
18	0 (50)	0 (40)	0 (160)	1.75±.0.11	0.495±0.04	0.721±0.05	1.400±0.13
19	0 (50)	0 (40)	0 (160)	1.69±0.14	0.476±0.02	0.728±0.03	1.410±0.06
20	0 (50)	0 (40)	0 (160)	1.76±0.12	0.479±0.03	0.718±0.02	1.390±0.06

$X_1 = (S-50)/10$, $X_2 = (M-40)/5$, $X_3 = (T-160)/20$

weighted and the absorbed water by the extrudates was determined. The rehydration ratio of the extrudates was calculated as the ratio of absorbed water by the extrudates to the initial weight of submerged samples (Mitra et al., 2019; Yu et al., 2013). Two replications for rehydration ratio for each sample was conducted and the average value of rehydration ratio of the samples was reported.

2.5. ***Developing artificial neural network (ANN) model***

2.5.1. ***ANN architecture and algorithm***

A most common artificial neural network (ANN) consists of input layer, hidden layer and output layer. Each layer is formed with many neurons and a neuron of one layer is connected with neurons of at least one other layer (Funes et al., 2015; Huang et al., 2007; Zurada, 1992). A feed-forward back-propagating algorithm is very common to develop predictive ANN model to predict the response variables as a function of independent variables (Mitra, et al., 2011; Zurada, 1992). In this study, an ANN structure as shown in Figure1 was constructed to develop a prediction model for the optimization of the soy protein isolate and corn flour blend formulations and extrusion processing variables for the desired physical properties of extrudates. The ANN structure consisting of one hidden layer with

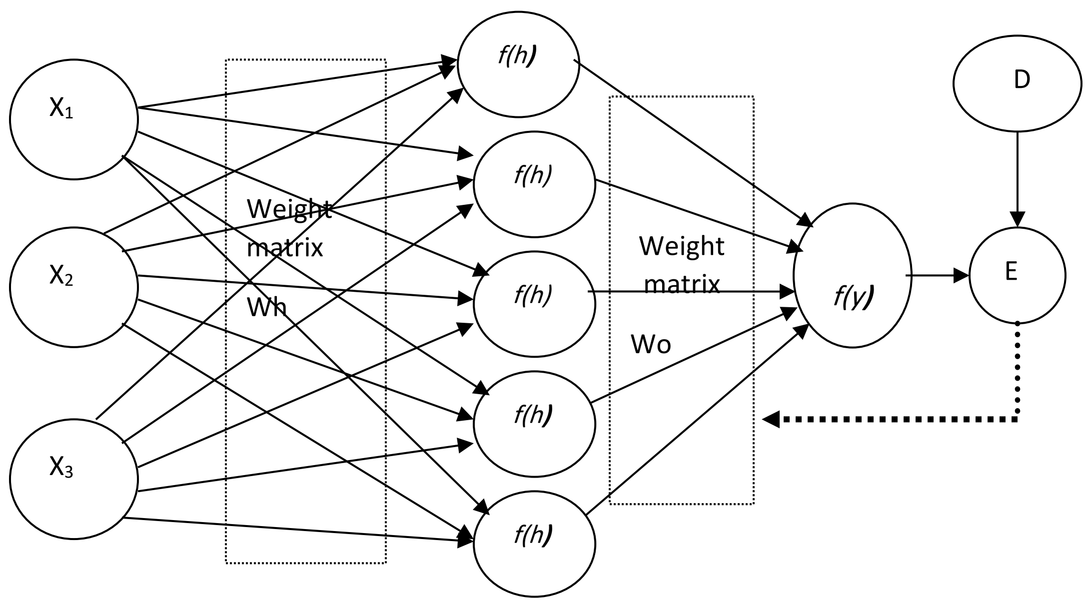

Figure 1. Architecture for developing ANN model to predict the physical properties of soy protein isolate and corn flour blend extrudates with the twin-screw extrusion processing variables (Mitra, et al., 2011).

five neurons was chosen to select the best prediction result. Multilayer ANN is needed for a very complex and special applications. But one hidden layer is sufficient to approximate any continuous nonlinear functions (Mitra, et al., 2011). The learning rate 0.5 was considered for this study because this low value of learning rate was chosen due to high fluctuations in error were observed at higher learning rates. The learning rate between 0 and 1 (generally 0.05η < η < 0.75, where η is the learning rate) is ideal for an ANN model development (Mitra, et al., 2011; Zurada, 1992). A feedforward backpropagation supervised learning algorithm was used to find suitable weights for a given input (x_i) and the network output (O) could match with the target output (D). In order to calculate weights and develop the ANN model all used equations and nomenclature are given under "Equations and the nomenclature for ANN modeling" at the end of the text. For a given input (soy protein isolate content/feed moisture content/extrusion temperature, x_i), the total weight (h_j) of the hidden layer was computed by the equation (1). Where the unit calculated the activity of ho_j using sigmoid function by the equation (2), whereas, w_{ji} = weight on the connection from ith unit to the jth unit, x_i = input, a = 0.2. Similarly, total weight (y) and output (O) of the output layer were estimated by the equation (3) and equation (4), respectively, where, wo_j = weight of jth layer. Once the activities of all outputs had been determined, the network computed the cycle error (E) using equation (5), where, D = target output (physical properties of extrudates).

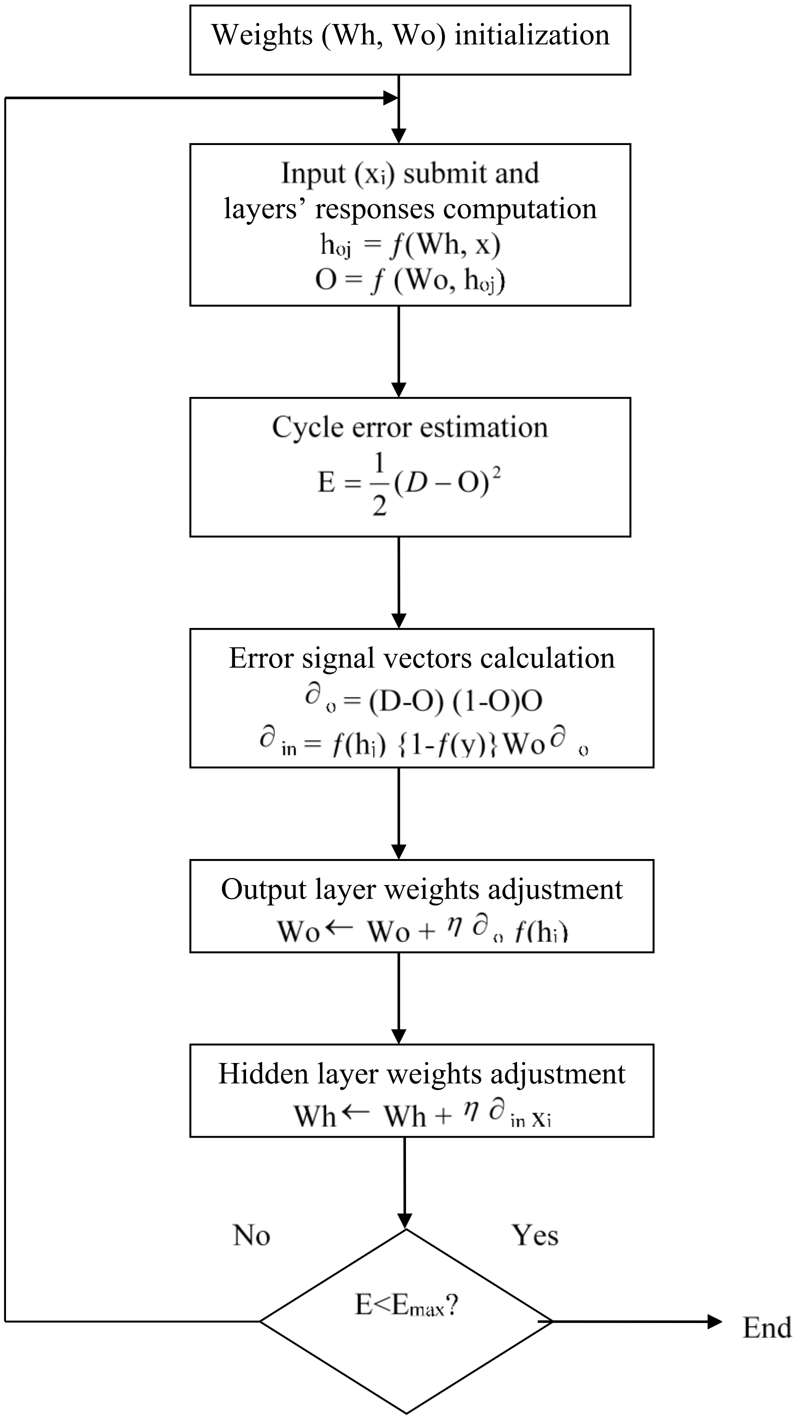

Figure 2. Flowchart of feedforward back propagation training algorithm to developed ANN model for predicting the physical properties of soy protein isolate and corn flour blend extrudates with the twin-screw extrusion processing variables (Mitra, et al., 2011).

2.5.2. ANN model development by training of ANN

Total 40 data points were used in this study. Twenty data collected from a literature (Yu et al., 2013) were used to train the artificial neural network. Another twenty data (Table 1) collected through this extrusion experiment were used for testing/validating the ANN model. A computing program was developed using MATLAB neural network toolbox to train the ANN and predict the physical properties (expansion ratio, piece density, breaking stress and rehydration ratio) of soy protein isolate and corn flour blend extrudates as a function of input data. The input data (independent variables/factors) were X_1(soy protein isolate content), X_2 (feed moisture content) and X_3 (extrusion temperature) to predict the target outputs (physical properties of extrudates). The ANN model's parameters were calculated by trial and error during the training of ANN. The training of the ANN started using a back-propagation training algorithm after constructing ANN architecture (Figure1). The training began with the feedforward recall phase as per the process described in Figure 2. The layers' responses h_{oj} and network outputs (O) were calculated in this phase after a single pattern vector x_i had been submitted at the input. Then, the error signal vector was determined in the output layer first, and then it was propagated toward the network input nodes. Weights were adjusted within the matrix (Wo) and then weights were adjusted within the matrix (Wh). The cumulative cycle errors of input to output mapping were calculated as a sum of overall continuous output errors in the entire training set. The final error value for the entire training cycle was calculated for the training data set. The training procedure ended when the final error value was lower than the upper bound of E_{max} (Zurada, 1992).

2.5.3. Testing /validation of ANN model

The trained ANN model was tested to justify the prediction capacity of physical properties of extrudates (expansion ratio, piece density, breaking stress and rehydration ratio) as a function of independent variables (soy protein isolate content, feed moisture content and extrusion temperature). The experimental 20 data points produced in this study were used to test the ANN model. The ANN outputs of training data set and prediction/testing data set were compared with experimental results of expansion ratio, piece density, breaking stress and rehydration ratio of soy protein isolate and corn flour blend extrudates.

3. Results and discussion

3.1. ANN model network optimization

The ANN model network was optimized using a trial-and-error method. In this case, six configurations for one hidden layer with 1-6 neurons of an ANN model network had been justified to determine an optimum ANN for the best prediction of physical properties of soy protein isolate and corn flour blend extrudate as a function of extrusion processing variables. The acceptable error (0.00001-0.000100) and the maximum iterations of the network were set to select the optimized network. The six different ANN networks and optimized weights (Wh and Wo) for one hidden layer with 5 neurons are shown in Table 2. The results shown in Table 2 indicated that the optimum network had one hidden layer with five neurons which had a minimum error and a minimum number of iterations for all physical properties of extrudates. The results indicated that the network iterations and network performance errors decreased with the increased hidden layer neurons from 1 to 5 but the network increased the iterations and the errors with 6 neurons of the hidden layer. However, variability of the acceptable errors and iterations varied depending on the physical properties of extrudates. Small number of neurons (1-4) of the network may not give the needed coverage during the training step. On the other hand, an excessive number of neurons (6) might lead the network to memorize the training patterns due to over fitting (Mitra, et al., 2011; Zurada, 1992). However, the range of errors (0.00001-0.000019) and the range of iterations (4400-27800) as shown in Table 2 fell under the acceptable set conditions. A network with a minimum final error in a minimal number of iterations during the training of the ANN should be selected as an adequate optimal ANN model (Huang et al., 2007; Mitra, et al., 2011; Zurada, 1992). Hence, the network of one hidden layer with 5 neurons was selected as the optimal ANN model for predicting the physical properties of soy protein and corn flour blend extrudates.

Table 2. ANN network optimization and optimized weights (Wh and Wo) for 1 hidden layer with 5 neurons

Extrudates Properties	Number of Hidden layer's neuron	Iterations	lowest error	Optimized Wh (5 hidden layer's neurons) X1	X2	X3	Optimized Wo (5 hidden layer's neurons)
Expansion ratio	1	30000	0.000025	0.13324	-1.69691	-2.54691	-5.47925
	2	30000	0.000011	0.34533	-0.71632	1.12233	-5.02495
	3	8400	0.00001	-1.7667	0.11797	1.14658	-4.62085
	4	5000	0.00001	0.67168	1.38396	-0.54128	-4.66411
	5	4400	0.00001	-0.17103	1.32892	0.60806	-4.49138
	6	10800	0.00001				
Piece density (g/mL)	1	30000	0.00002	-0.04724	0.03979	0.39063	-5.37403
	2	30000	0.000018	1.91073	-1.53788	2.61051	-5.24737
	3	30000	0.000015	-0.63085	0.66275	-0.21814	-4.63721
	4	30000	0.000014	-0.88311	1.02173	-0.53031	-4.69494
	5	12300	0.000013	-0.62224	0.78231	-0.22803	-4.53793
	6	30000	0.000014				
Breaking stress (MPa)	1	30000	0.000394	9.07989	-1.9429	-5.39813	-4.91074
	2	30000	0.000052	3.23278	-8.07301	3.07025	-3.90182
	3	30000	0.000019	-9.2841	3.05145	3.53142	-4.10501
	4	30000	0.000029	0.57356	6.49649	-6.22507	-3.81773
	5	27500	0.000016	-4.31001	6.63785	-2.0435	-3.33749
	6	30000	0.000026				
Rehydration ratio	1	30000	0.000102	-0.40235	-5.34267	-2.48583	-5.44974
	2	30000	0.000048	2.31774	-0.27109	3.55926	-4.64688
	3	30000	0.000026	-2.98528	0.43278	-3.20823	-4.24295
	4	30000	0.000022	-0.37218	5.05064	-1.51479	-4.25555
	5	27800	0.000019	-0.02598	4.29957	-0.79728	-3.94489
	6	30000	0.000021				

3.2. ANN model performance evaluation

The training/learning phase and the testing/validation phase are basic two steps to develop an ANN model. The correlation between training data set and the ANN training outputs and the correlation between experimental and testing prediction of optimized ANN model outputs for expansion ratio, piece density, breaking stress and rehydration ratio of soy protein isolate and corn flour blend extrudates are shown in Figure 3 and Figure 4, respectively. The results indicated that correlation coefficient (R^2) associated with training data set and ANN training outputs were 0.93, 0.95, 0.97 and 0.95 (Figure 3) and with experimental data and ANN prediction were 0.89, 0.94, 0.98 and 0.93 (Figure 4) for expansion ration, piece density, breaking stress and rehydration ratio of extrudates, respectively. The correlation coefficient for the testing set was very close to the training set. The results indicated that the trained optimized ANN model could predict the physical properties of soy protein isolate and corn flour blend extrudates with an accuracy of 89-98% depending on the physical properties extrudates tested. The network weights and coefficients associated with this ANN model were calculated with the codes of a computer program written in MATLAB and the calculated results of the optimized network were presented in Table 2. The developed simplified ANN model to predict expansion ratio, piece density, breaking stress and rehydration ratio of extrudates as a function of the extrusion processing independent variables (soy protein isolate content, feed moisture content and extrusion temperature) was scant in the literature and was user friendly.

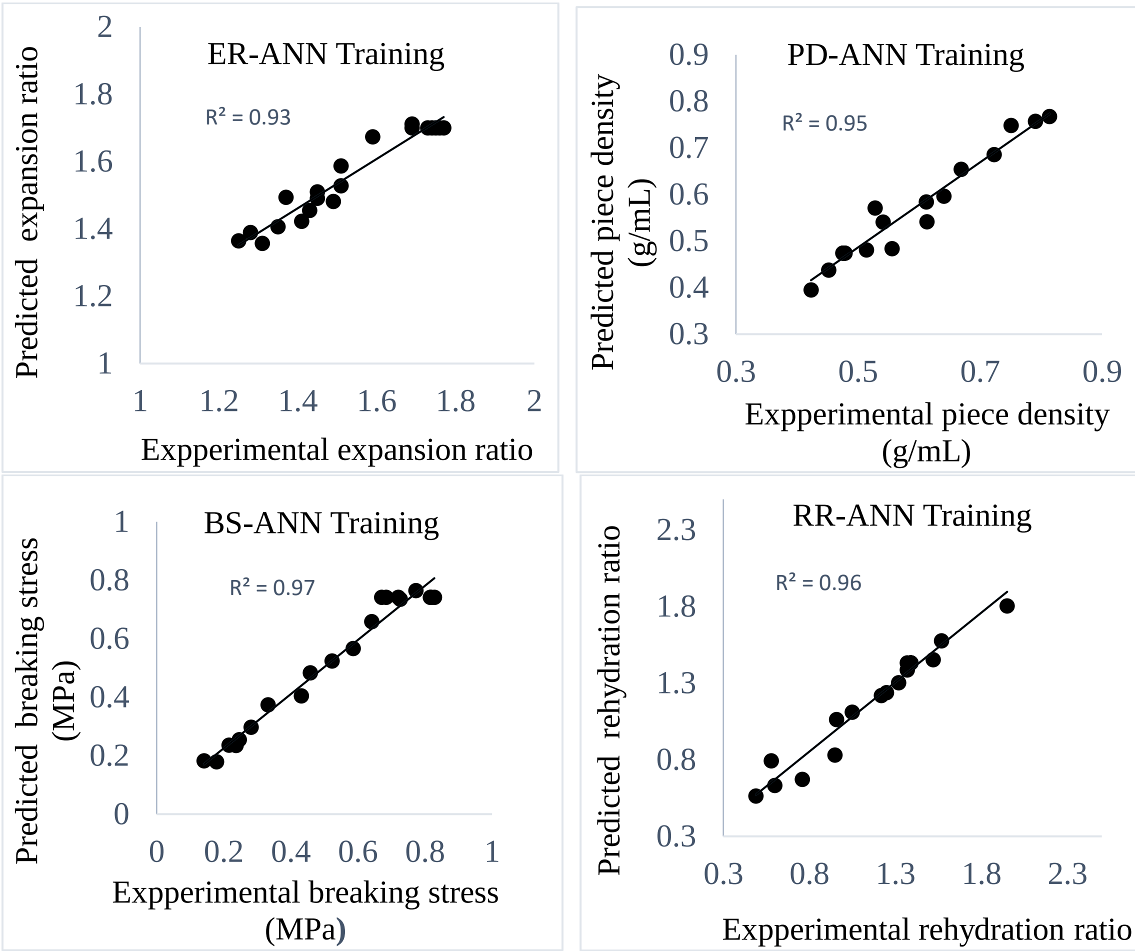

Figure 3. Correlation between training data set and optimum neural network outputs of expansion ratio (ER), piece density (PD), breaking stress (BS) and rehydration ratio (RR) of soy protein isolate and corn flour blend extrudates.

3.3. Statistical validation of the developed ANN model

An extensive statistical analysis of training data set and the testing data set was conducted to determine the statistical similarity between the prediction outputs of ANN training and testing performance. The statistical results indicated that the statistical parameters of the ANN model predictions were close to those of the desired values for the training and testing sets. A t-test had been conducted to determine whether the difference of the mean between the two groups was significant or not. In this case, the associated probability was greater than 0.05. Hence, the difference in the mean of the desired and predicted values was statistically insignificant. Similarly, an F value had been determined to justify the significance of the difference of standard deviation of two groups. The relevant probability was higher than 0.05. Hence, the standard deviation of the two groups also does not differ significantly (Mitra, et al., 2011).

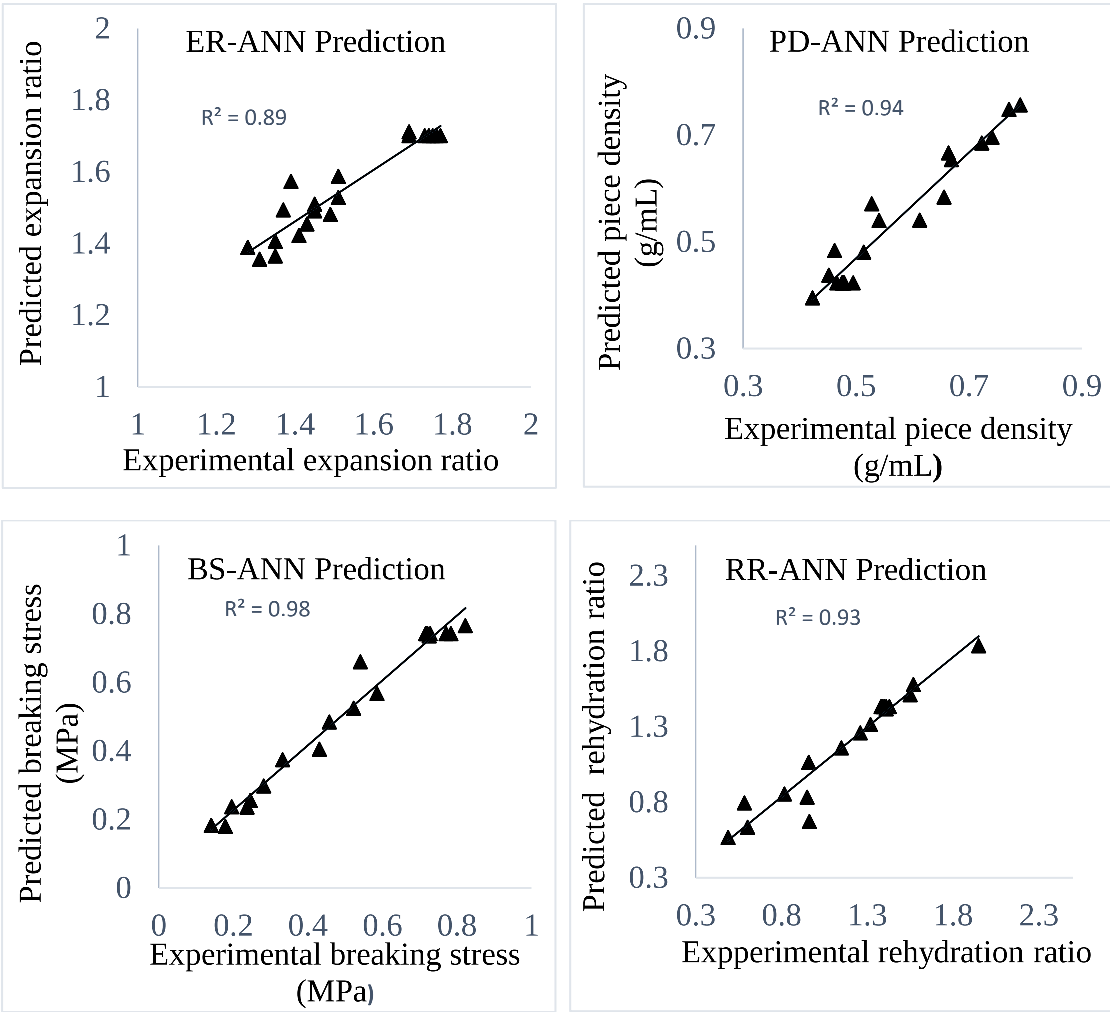

Figure 4. Correlation between experimental and ANN model testing prediction of expansion ratio (ER), piece density (PD), breaking stress (BS) and rehydration ratio (RR) of soy protein isolate and corn flour blend extrudates.

3.4. Comparison ANN model prediction with experimental data

Twenty different soy protein isolate and corn flour blend extrudates were produced as per the CCRD. The physical properties expansion ratio, piece density (g/mL), breaking stress (MPa) and rehydration ratio of the extrudates were determined and the results were summarized in Table 1. The experimental data of Table 1 (expansion ratio, piece density, breaking stress and rehydration ratio of soy protein isolate and corn flour blend extrudates) and the ANN model prediction results are shown in Figure 5. The ANN model showed its potential to predict response variables expansion ratio, piece density, breaking stress and rehydration ratio of soy protein isolate and corn flour blend extrudates as a function of soy protein isolate content, feed moisture content and extrusion temperature. However, the prediction accuracy varied (89-98%) depending on the physical properties of extrudates. The prediction accuracy variation (9%) happened among the physical properties of extrude due to the variation of experimental errors for the replicated central experimental points. It was observed (expansion ratio of Figure 5) that the higher fluctuation in the central point was occurred and this caused the lower prediction accuracy. This result indicated that the ANN prediction can be improved by minimizing experimental errors of the replicated data for the same experimental point.

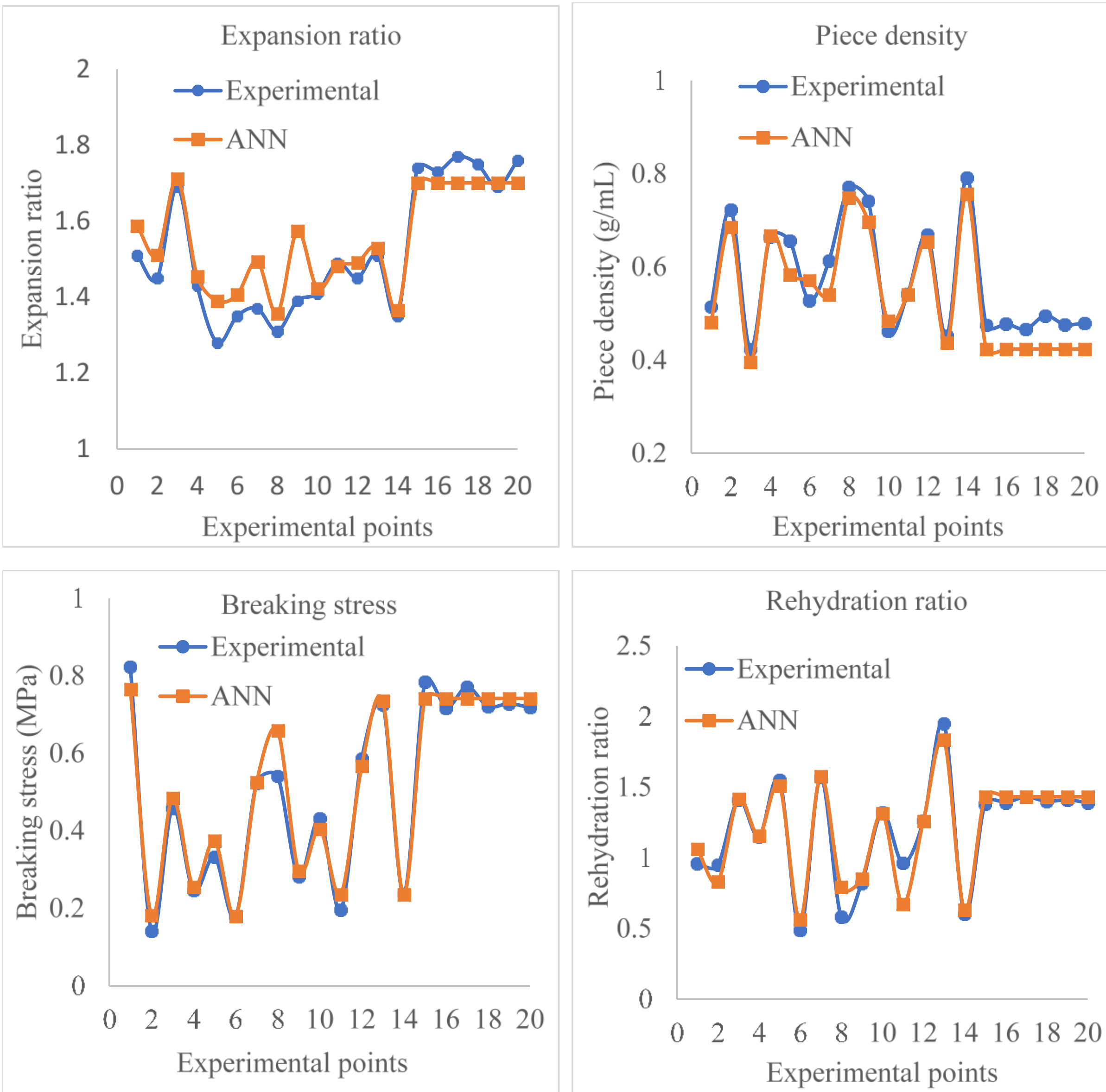

Figure 5. Comparison ANN predictions with experimental expansion ratio, piece density, breaking stress and rehydration ratio of soy protein isolate and corn flour blend extrudates.

4. Conclusions

55-60% soy protein isolate could be incorporated with corn flour to develop protein rich soy protein isolate and corn flour blend cereal like products through twin screw extrusion processing. The developed ANN model, consisting of one hidden layer with 5 neurons, was able to predict physical properties expansion ratio, piece density, breaking stress and rehydration ratio of extrudates from the factors (soy protein isolate content, feed moisture content and extrusion temperature) with an 89-98% accuracy depending on the physical properties of extrudates. The prediction of the physical properties of extrudates using this ANN model was a simple, convenient, and accurate method.

Equations and the nomenclature for ANN modeling

$$h_j = \sum_{i=1}^{3} Wh_{ji} x_i \quad (1)$$

$$ho_j = f(h_j) = \frac{1}{1+exp^{-ah_j}} \quad (2)$$

$$y = \sum_{j=1}^{5} Wo_j ho_j \quad (3)$$

$$O = f(y) = \frac{1}{1+exp^{-ay}} \quad (4)$$

$$E = \frac{1}{2}(D-O)^2 \quad (5)$$

∂_o = (D-O) (1-O)O (6)

Wo = Wo + $\eta\, \partial_o$ f(h_j) (7)

∂_{in} = f(h_j) {1-f(y)}Wo ∂_o (8)

Wh = Wh + $\eta\, \partial_{in} x_i$ (9)

Where,
h_j = Total weight of hidden layer
Wh_{ji} = weight on the connection from ith unit to the jth unit
X_i = Input (X_1 – percent of soy protein content, X_2- percent of moisture content and X_3- extrusion temperature)
ho_j = Layer's response, a (steepness factor of the continuous activation function) = 0.2
Wo_j = weight of jth layer
y = Total weight of output layer
O = output of the output layer
E = Cycle error
D = Target output (physical properties of extrudates)
∂_o and ∂_{in} = Error signal vectors

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