African Journal of Agricultural Research Vol. 5 (1), pp. 070-077, 4 January, 2010
Available online at http://www.academicjournals.org/AJAR
DOI: 10.5897/AJAR09.222

Full Length Research Paper

Neural network approach for modeling the mass transfer of potato slices during osmotic dehydration using genetic algorithm

M. R. Amiryousefi* and M. Mohebbi

Department of Food Science and Technology, Ferdowsi University of Mashhad, P. O. Box: 91775-1163, Mashhad, Iran.

Accepted 19 November, 2009

In this study, an approach for designing a neural network based on genetic algorithm has been used to model mass transfer during osmotic dehydration of potato slices. The experimental data were obtained through a complete randomized design with different osmotic solutions (5, 10 and 15% w/w) and potato to solution ratios (1:6, 1:8 and 1:10) at varying temperatures (30, 40 and 60°C) and the best model obtained with optimization of a multi-layer perceptron neural network had a mean absolute error of 0.260, 0.516 and 0.137 for moisture content, water loss and solid gain of osmotically dehydrated slices respectively.

Key words: Osmotic dehydration, potato, neural network, genetic algorithm, modeling, mass transfer.

INTRODUCTION

Potato (*Solanum tuberosum*) is an herbaceous annual that grows up to 100 cm tall and produces a tuber so rich in starch that ranks as the world's fourth most important food crop, after maize, wheat and rice (Lisińska et al., 1989).

The technique of food dehydration is probably the oldest method of food preservation. The main purpose of drying is to allow longer periods of storage, minimize packaging requirement and reduce shipping weights. It is defined as a process of moisture removal due to simultaneous heat and mass transfer (Hernandez-Perez et al., 2004).

Osmotic dehydration is a special method of drying which is based on the principle that when cellular material are immersed in a hypertonic aqueous solution, a driving force for water removal sets up because of the higher osmotic pressure of the hypertonic solution. There are two major counter-current flows during osmotic dehydration, that is, water flows out of the food into the solution and likewise solute is transferred from the solution into the food (Azuara et al., 2002; Rastogi et al., 2004).

The influences of the main variables in osmotic dehydration, including concentration, composition of the osmotic solution, temperature, immersion time, pre-treatments, nature of food and solution to sample ratio on mass transfer has been established in many researches (Yao et al., 1996).

Osmotic dehydration can be modeled by mechanistic approaches. However soft-computing methods such as neuro-genetic modeling may be suitable for description of mass transfer in biological materials such as food with ill-defined characteristics. Artificial neural network (ANN) models recently have been used in the bio-processing problems including description the air-drying behavior of different natural materials such as carrot, ginseng, cassava and mango (Baughman et al., 1995; Erenturk et al., 2004; Hernandez-Perez et al., 2004; Kerr et al., 2006; Martynenko et al., 2006; Erenturk et al., 2007). Neural networks generally consist of a number of interconnected processing neurons. Determination of a neural network structure is a crucial step in neural network modeling. Multi-layer perceptron (MLP) is probably the best known type of neural network with three layers: an input layer, an output layer and hidden layer(s) and information is propagated in a forward direction with no loops. Learning algorithms for neural networks training can be classified

*Corresponding author. E-mail: mramiryousefi@yahoo.com.

in two main groups: supervised and unsupervised algorithms. Adjustment of the strength or weights of the inter-neuron connection according to difference between the desired and actual network outputs corresponding to a given input is carried out in a supervised learning algorithm such as back propagation. Genetic algorithm is one of the suitable algorithms for training MLPs (Jang et al., 1997; Martinenko, 2006; Desai, 2008).

Genetic algorithm (GA) is a probabilistic optimization algorithm guided by the mechanics of natural evolution according to Darwinian theory of evolution. Evolutionary algorithms have proven highly effective for achieving optimal or near optimal solutions to many complex real-world optimization problems and several studies have discussed the advantages of genetic algorithm derived back propagation neural networks (Maniezzq, 1994; Jang et al., 1997; Perrot et al., 1998; Jiang et al., 2003; Huang et al., 2009; Samanta et al., 2003; Ko et al., 2009).

In this work, a genetic algorithm optimized neural network was used to model moisture content (MC), water loss (WL) and solid gain (SG), obtained experimentally through osmotic dehydration of potato slices. The proposed model can investigate the dependence of mass transfer kinetics (WL and SG) as well as moisture content of dehydrated potato slices on different osmotic conditions and study the effectiveness of genetic algorithm in optimization of neural network structure.

MATERIALS AND METHODS

Materials

Ripe potatoes were purchased from local market. Thoroughly washed and peeled potatoes were cut into slices, 6 mm in thickness using a stainless steel knife. An aluminum mould was used to prepare rectangular cubes of dimensions 3 cm × 2 cm × 6 mm. The average moisture content of potatoes was found to be 87.9 ± 0.8% on wet basis (AOAC, 1990). Salt, as the osmotic agent, was prepared from food grade samples.

Osmotic dehydration

Osmotic dehydration was carried out by immersion of potato slices in osmotic solution of 5, 10 and 15% w/w concentration. Vessels containing osmotic solutions were placed in controlled incubator at varying temperatures (30, 40 and 60°C) and different potato to solution ratios (1:6, 1:8 and 1:10). The incubator was run without the samples for about 30 min to set the desired conditions before each drying experiment. Dehydration process started when desired temperature were achieved. During dehydration period (4 h), samples were taken at 1 h intervals. Each experiment consisted of 3 experimental runs; at each time interval, triplicate samples were used. were drained and were wiped dry with absorbent paper. Upon removal from the osmotic solution, potato slices

The average moisture content and dry matter of 3 repli-cates for each treatment were determined by drying at 105°C for 24 h in an oven.

Calculations

Water loss and solid gain of samples after osmotic dehydration were determined as follows:

$$\%WL = \frac{(M_i - M_o)}{W_i} \times 100 \quad (1)$$

$$\%SG = \frac{(S_i - S_o)}{W_i} \times 100 \quad (2)$$

Where; Mi = moisture content of fresh sample (g); Mo = moisture content of osmotically treated sample (g); Si= solid content of fresh sample (g); So= solid content of osmotically treated sample (g); So = solid content of fresh sample (g); Wi = total weight of fresh sample (g).

Neural networks modeling and genetic algorithm optimization

Two important factors must be considered in order to ensure a successful modeling of MLP. First, is the number of hidden layers and second is the number of neurons in each hidden layer. Since almost all of the problems in neural network modeling could be solved with one hidden layer (Erenturk et al., 2007; Movagharnejad et al., 2007; Ko et al., 2009), an ANN with three layers was used in this research.

In total, 324 data were collected for the four different osmotic times and three osmotic temperatures, concen-trations and ratios. First, the data order was randomized and then the data were divided into three partitions. The first partition (training data) was used to perform the training of the network (40% of data). The second one (cross validation data) was used to evaluate the prediction quality of the network during the training (30% of data). For the purpose of estimating the performance of the trained network on new data, a third partition, which never was seen by the artificial neural network during the training and cross-validation process, was used (30% of data) for testing.

The training process was carried on for 1,000 epochs or until the cross-validation data's mean squared error (MSE), calculated by Equation 3 and did not improve for 100 epochs to avoid over fitting of the network.

Back propagation algorithm was used to implement supervised training of the network. Back propagation is based on searching an error surface (error as a function of ANN weights) using gradient descent for point(s) with minimum error. Each iteration in back propagation constitutes two sweeps: forward activation to produce a solution and the backwards propagation of the computed error to modify the neurons' weights (Movagharnejad and Nikzad, 2007).

Testing was carried out with the best weights stored during the training. Evaluation of the performance of the trained network was based on the accuracy of the network in the test partition. Therefore, MSE, normalized mean-squared error (NMSE), mean absolute error (MAE) and correlation coefficient (r) for each output were calculated by using Equations 3 - 7 (Mohebbi et al., 2008) based on testing data and were used to compare the performance of different ANN architectures. In this study, modeling of mass transfer during osmotic dehydration was carried out with Neurosolution for Excel software release 5.0, produced by NeuroDimension, Inc. The design of applied ANN is given in Figure 1.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N} (O_i - T_i)^2}{N} \quad (3)$$

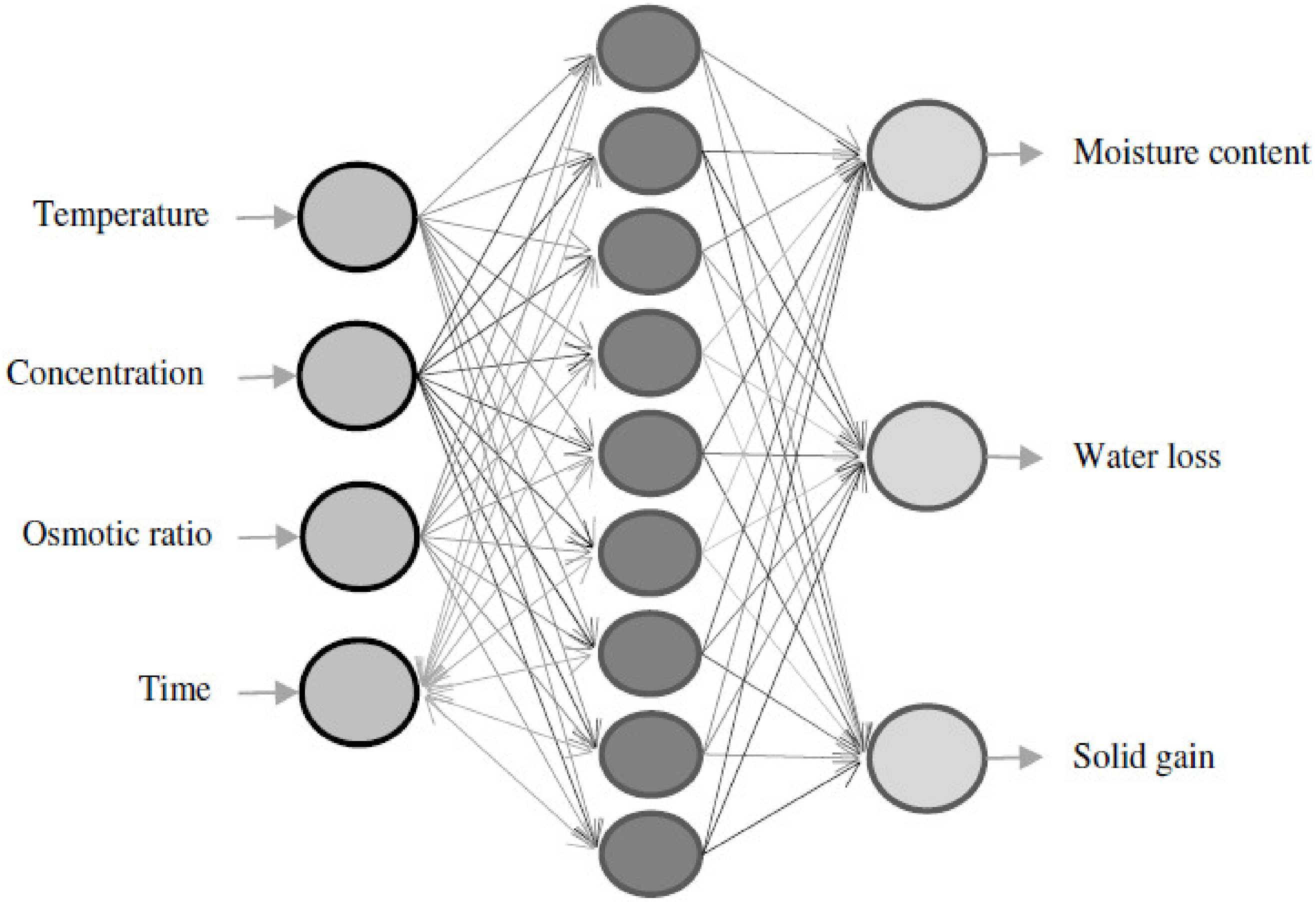

Figure 1. Fully connected three-layered MLP network with 9 neurons in the .hidden layer.

$$\mathrm{NMSE} = \frac{1}{\sigma^2}\frac{1}{N}\sum_{i=1}^{N}(O_i - T_i)^2 \quad (4)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|O_i - T_i\right| \quad (5)$$

$$\mathrm{r} = \sqrt{1 - \frac{\sum_{i=1}^{N}[O_i - T_i]^2}{\sum_{i=1}^{N}[O_i - T_m]^2}} \quad (6)$$

Where; Oi is the desired output for cross validation data i and Ti is the network for cross validation data i and N is the number of data, σ2 is the variance, and

$$T_m = \frac{\sum_{i=1}^{N} O_i}{N} \quad (7)$$

Statistical analysis

Analysis of variance (ANOVA) of data was performed using a statistical program called "MSTAT" version C, and determination of significant differences of means was carried out by "Duncan" test at 5% significant level using the above software program.

RESULTS AND DISCUSSION

Effect of osmotic dehydration on mass transfer kinetics

Average values of MC, WL and SG after osmotic dehydration of potato slices for the whole treatments are presented in Table 1.

In Table 2, parts of ANOVA tables for MC, WL and SG are given. It was found that WL and SG increased and MC decreased significantly as temperature, concentration, potato to solution ratio and osmotic duration increased. Therefore, samples immersed in osmotic solution of 15% with potato to solution ratio of 1:10 at 60ºC and for 4 h had the minimum MC (67.6%) and greatest WL (45.54%) and SG (8.31%).

Increasing WL and SG and also decreasing MC by

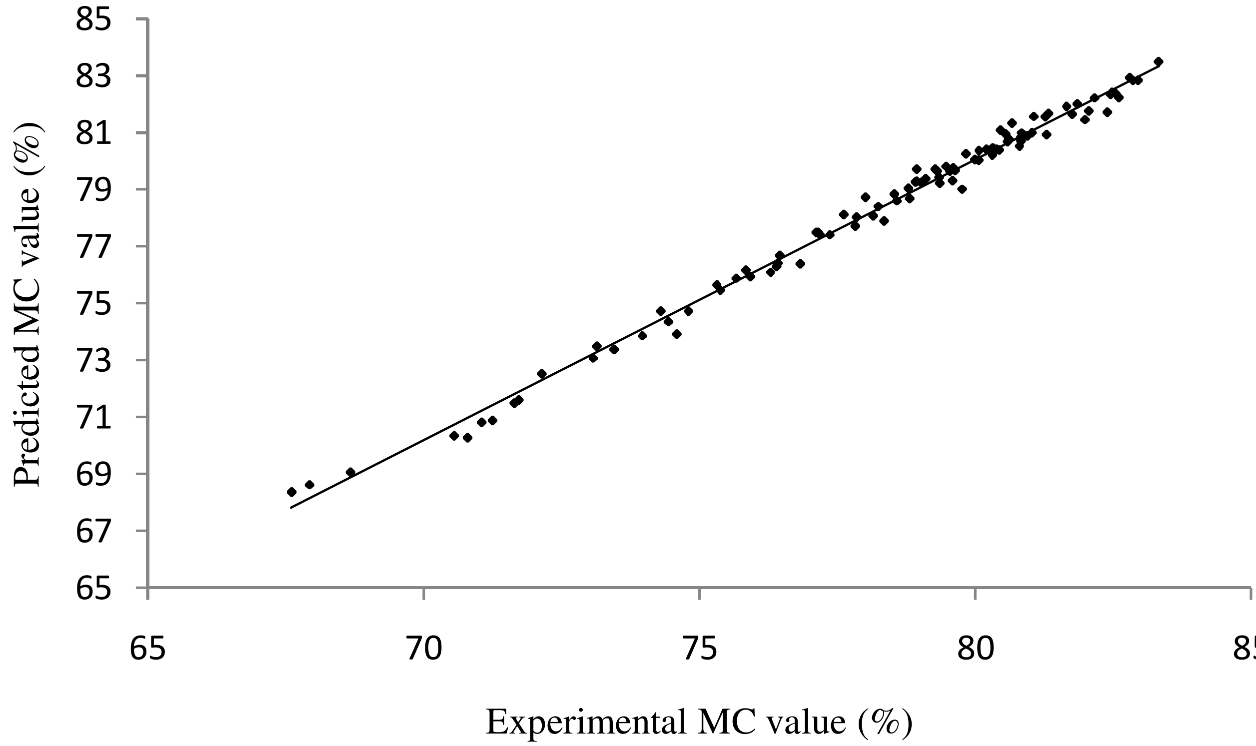

Figure 2. Experimental vs. predicted values for moisture content of osmotically dehydrated potato by optimum GA-NN configuration (R = 0.996).

increasing temperature could be attributed to the effect of temperature on the membrane permeability by making it more permeable to water and salt exchanges. On the other hand, by increasing salt concentration, the osmotic pressure in the potato tissue is increased, which leads to increase of WL and SG and therefore decreasing MC. It is clear that raising the quantity of osmotic solution to potato samples results in enhancement of mass transfer and therefore decrease in MC of osmotically dehydrated potato slices.

Artificial neural network optimization

Optimization of neural network structure is usually carried out with trial and error, while in this research, determination of the number of neurons in the hidden layer(s), the momentum and learning rate was accomplished with genetic algorithm. Table 3 depicts specification of the algorithm applied in this research. It must be emphasized that population size and number of generations affect the processing time because the fitness value must be calculated for every chromosome in each generation. Summary of the network architecture in hidden layer(s) by genetic algorithm method is given in Table 4.

Table 5 reports the performance of optimized networks in terms of mean square error (MSE), normalized mean square error (NMSE), mean absolute error (MAE), minimum absolute error (Min Abs Error), maximum absolute error (Max Abs Error) and the linear correlation coefficient (r) between experimental data and neural network outputs for testing data set.

In Figures 2 - 4 MC, WL and SG of experimental data versus neural network outputs are shown which illustrate good agreement.

Conclusion

The following conclusions are drawn from the investigation on osmotic dehydration of potato slices and the possibility of application of artificial neural network optimized with genetic algorithm to predict mass transfer kinetics of osmotically dehydrated potato slices:

1. Solid gain and water loss increased and also moisture content decreased significantly when osmotic temperature, concentration, potato to solution ratio and immersion time increased. The effect of temperature was more than the others.
2. A multilayer feed forward neural network based on four inputs (operation conditions) and 9 neurons in the single hidden layer was found to be the best model for predicting MC, WL and SG which showed minimum MSE (0.109, 0.395 and 0.030, respectively) and high r (0.996, 0.990 and 0.997, respectively) values.

Table 1. Means and standard deviations of MC, WL and SG during osmotic dehydration of potato slices at different concentrations (C), temperatures (T), immersion times (h) and potato to solution ratios.

T (ºC)	Brix	Ratio	M (%)				WL (%)				SG (%)			
			1h	2h	3h	4h	1h	2h	3h	4h	1h	2h	3h	4h
30	5	1:10	83.32±0.01	83.08±0.11	81.81±0.06	82.06±0.13	26.61±0.26	26.6±0.72	31.54±0.79	30.06±0.24	0.26±0.06	0.48±0.05	0.53±0.23	0.64±0.06
30	10	1:6	82.86±0.42	82.55±0.4	81.05±0.25	81.3±0.35	27.29±0.69	27.53±0.97	32.73±0.52	31.09±0.51	0.53±0.23	0.75±0.15	0.89±0.09	1.06±0.19
30	10	1:8	82.45±0.26	81.84±0.39	80.67±0.39	80.82±0.29	28.15±0.08	28.98±0.38	33.46±0.46	31.66±0.04	0.71±0.21	1.06±0.26	1.04±0.21	1.34±0.24
30	15	1:6	81.03±0.15	80.8±0.33	79.64±0.41	79.76±0.34	31.23±0.48	31.18±0.17	35.08±0.55	33.88±0.55	1.26±0.24	1.48±0.33	1.5±0.2	1.7±0.15
30	15	1:8	80.83±0.1	80.43±0.25	79.27±0.38	79.35±0.06	32.21±0.16	31.81±0.34	35.64±0.41	34.84±0.01	1.2±0.05	1.64±0.14	1.66±0.21	1.8±0.05
30	15	1:10	80.39±0.19	80.31±0.32	79.3±0.49	78.92±0.23	33.5±0.3	32.5±0.5	35.61±0.56	35.71±0.21	1.26±0.09	1.58±0.15	1.64±0.26	1.94±0.14
40	5	1:6	83.33±0.14	82.95±0.18	81.75±0.04	80.2±0.08	25.08±0.07	25.78±0.25	28.45±0	31.2±0.15	0.56±0.11	0.76±0.11	1.26±0.04	1.99±0.04
40	5	1:8	82.8±0.21	82.6±0.23	80.84±0.13	79.6±0.19	26.41±0.36	26.79±0.66	31.54±0.36	33±0.2	0.76±0.11	0.86±0.06	1.35±0.03	2.06±0.11
40	5	1:10	82.48±0.04	82.39±0.21	80.32±0.15	78.94±0.09	27.66±0.11	27.95±0.4	33.14±0.16	34.75±0.2	0.79±0.06	0.8±0.1	1.41±0.09	2.18±0.03
40	10	1:6	82.16±0.08	81.99±0.17	80±0	78.58±0.07	28.64±0.21	28.91±0.36	33.39±0.19	35.01±0.01	0.86±0.11	0.95±0.23	1.63±0.05	2.41±0.06
40	10	1:8	81.26±0.36	80.94±0.12	79.54±0.06	78.24±0.26	30.06±0.51	30.44±0.04	33.85±0.18	35.15±0.5	1.33±0.2	1.53±0.1	1.9±0.1	2.66±0.09
40	15	1:6	79.83±0.14	79.1±0.46	78.35±0.39	76.83±0.11	33.95±0.18	34.6±0.52	35.5±0.48	37.25±0.22	1.63±0.08	2.08±0.25	2.48±0.2	3.28±0.02
40	15	1:8	79.47±0.4	78.78±0.4	77.83±0.22	76.39±0.25	34.26±0.36	34.98±0.25	36.43±0.08	37.98±0.13	1.85±0.25	2.25±0.28	2.66±0.16	3.43±0.18
40	15	1:10	79.34±0.22	78±0.8	77.15±0.63	75.84±0.53	34.55±0.2	35.54±0.46	37.11±0.51	38.45±0.4	1.89±0.14	2.76±0.56	3.04±0.39	3.75±0.33
60	5	1:6	80.6±0.4	78.94±0.3	77.11±0.31	74.29±0.58	27.15±0.35	29.41±0.31	32.35±0.18	35.95±0.57	2.61±0.29	3.6±0.2	4.49±0.24	5.98±0.35
60	5	1:8	80.06±0.16	78.53±0.19	76.42±0.23	73.13±0.29	28.51±0.26	30.1±0.3	33.18±0.43	37.75±0.12	2.79±0.21	3.8±0.1	4.89±0.09	6.43±0.23
60	5	1:10	79.59±0.13	77.85±0.05	75.38±0.44	72.14±0.18	29.83±0.23	31.79±0.24	35.23±0.72	39.45±0.2	2.89±0.06	3.96±0.11	5.2±0.17	6.71±0.09
60	10	1:6	78.8±0.05	77.19±0.33	74.8±0.14	71.72±0.09	31.28±0	32.95±0.48	36.29±0.11	39.88±0	3.23±0.05	4.24±0.16	5.39±0.09	6.94±0.09
60	10	1:8	78.15±0.12	76.46±0.01	74.58±0.38	71.24±0.03	32.63±0.13	34.35±0.22	37.14±0.21	40.35±0	3.45±0.07	4.49±0.06	5.3±0.27	7.2±0.03
60	10	1:10	77.36±0.1	75.66±0.22	73.07±0.37	70.79±0.21	34.19±0.09	35.94±0.04	39.36±0.46	41.05±0.07	3.71±0.11	4.71±0.19	5.89±0.16	7.34±0.16
60	15	1:6	76.29±0.17	74.44±0.1	71.64±0.34	68.67±0.11	36.26±0.16	38.08±0.08	41.59±0.36	44.64±0.06	4.05±0.1	5.11±0.11	6.34±0.16	7.75±0.08
60	15	1:8	75.92±0.34	73.97±0.61	71.05±0.18	67.93±0.15	36.95±0.12	38.78±0.83	42.48±0.05	45.25±0.07	4.16±0.26	5.29±0.26	6.51±0.14	8.15±0.1
60	15	1:10	75.31±0.29	73.45±0.14	70.55±0.27	67.6±0.03	37.49±0.11	39.29±0.14	43.03±0.38	45.54±0.09	4.53±0.23	5.58±0.07	6.74±0.09	8.31±0.01

Table 2. Successive mean squares from the analysis of variance of the MC, WL and SG

Source	Degree of freedom	Mean square		
		MC	WL	SG
A	2	1327.03**	964.99**	538.44**
B	2	369.97**	1281.46**	50.79**
C	2	29.43**	117.80**	3.72**
D	3	244.43**	578.87**	52.35**
A×B	4	8.88**	13.62**	0.48**

Table 2. Contd.

A×C	4	0.87**	0.42*	0.22**
A×D	6	43.75**	35.07**	13.94**
B×C	4	0.35**	5.00**	0.11*
B×D	6	0.21*	5.52**	0.12**
C×D	6	0.04NS	0.47**	0.03NS
Error	216	0.09	0.15	0.04
Total	323			

A osmotic temperature, B osmotic concentration, C osmotic ratio, D osmotic time, NS not significant
**p = 0.01; *p = 0.05.

Table 3. Applied genetic algorithm properties.

Number of population	1000
Population size	100
Cross over	1 point
Cross over probability	0.9
Mutation	Uniform
Mutation probability	0.01

Table 4. Structure of optimized neural network.

Number of hidden layer(s)	Number of neurons in hidden layer	Momentum rate	Learning rate
1	9	0.875	0.721

Table 5. Performance of GA-NN for modeling of moisture content, water loss and solid gain, in osmotically dehydrated potato slices.

Performance	%MC	%WL	%SG
MSE	0.109	0.395	0.030
NMSE	0.008	0.020	0.007
MAE	0.260	0.516	0.137
Min Abs Error	0.0016	0.0054	0.0052
Max Abs Error	0.76	1.44	0.49
r	0.996	0.990	0.997

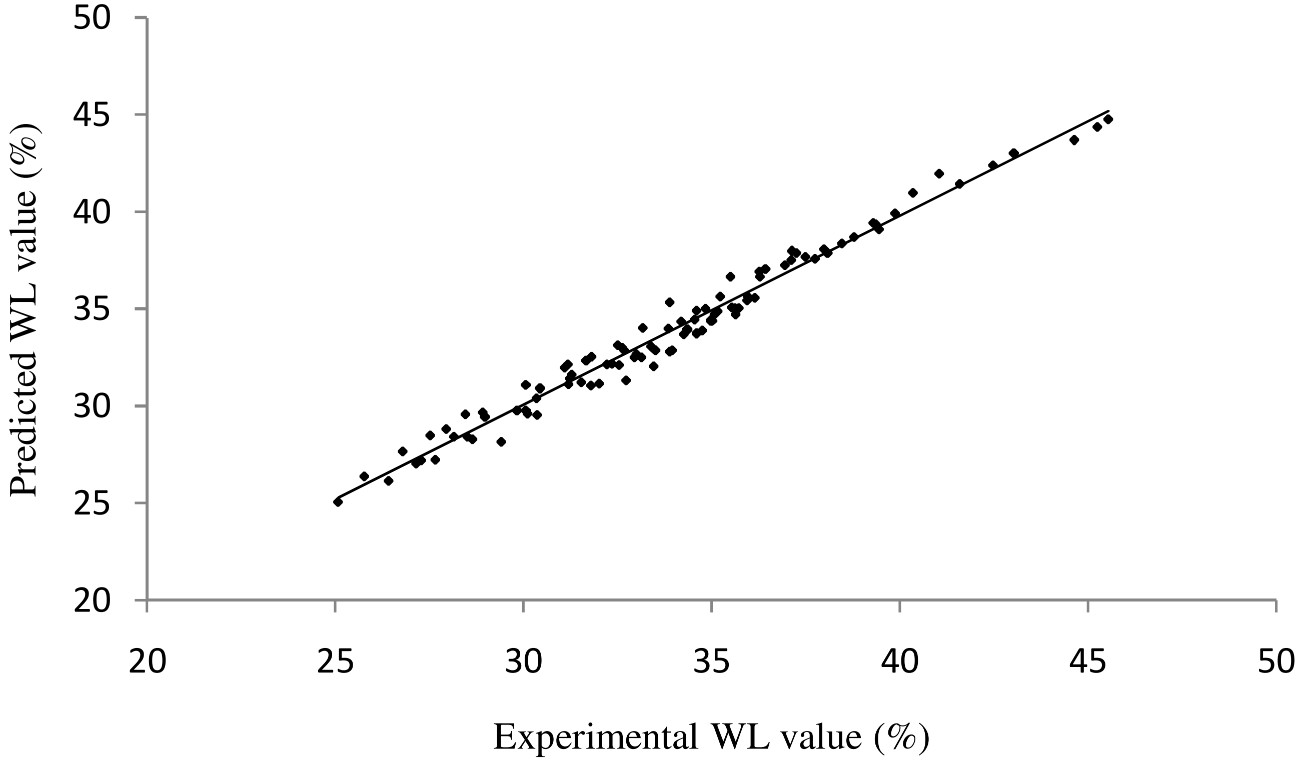

Figure 3. Experimental vs. predicted values for water loss of osmotically dehydrated potato by optimum GA-NN configuration (R = 0.990).

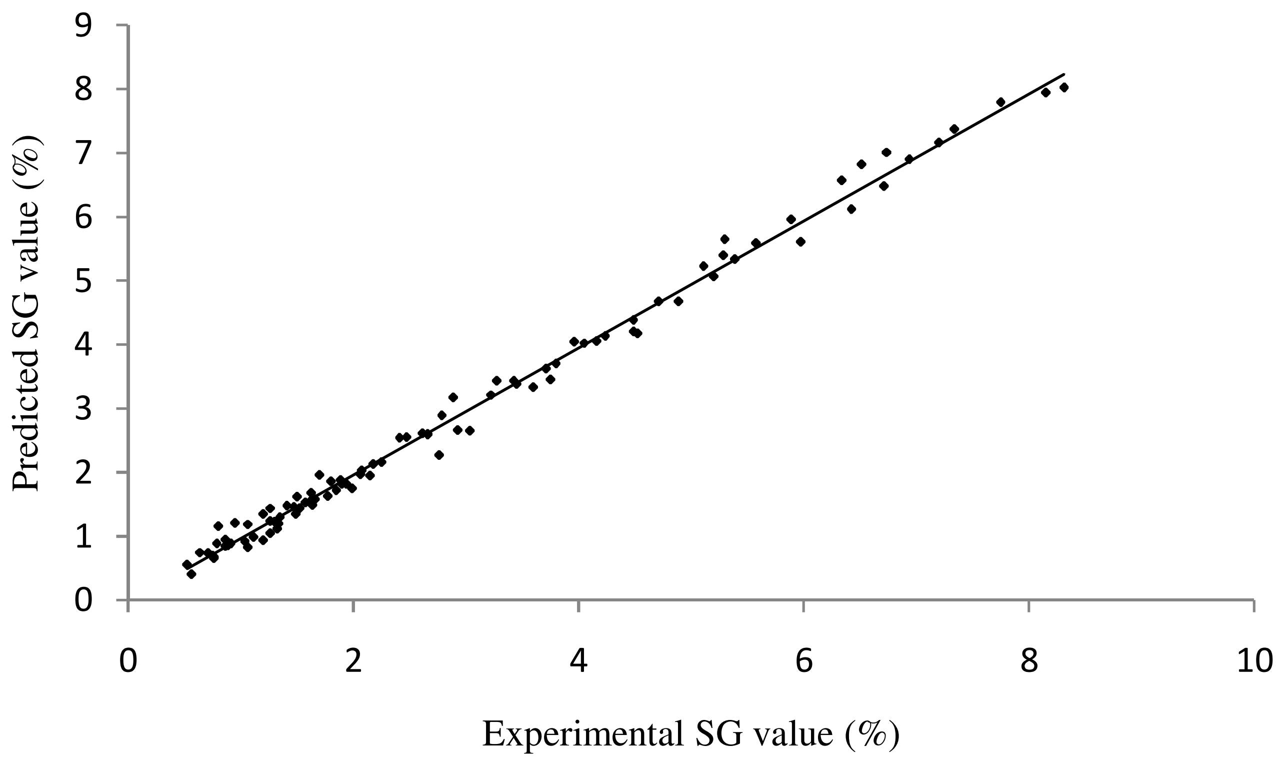

Figure 4. Experimental vs. predicted values for solid gain of osmotically dehydrated potato by optimum *GA-NN* configuration (R = 0.997).

3. It is clear from the results that optimized ANN model describes mass transfer during osmotic dehydration well and it is found that genetic algorithm is a good alternative over trail and error approach for quick and efficient determination of optimal ANN structure. This methodology can be applied to optimize the operating conditions regarding different state variables.

ACKNOWLEDGMENT

The authors are thankful to Dr. Mazaheri Tehrani for his support during the experiments.

REFERENCES

AOAC (1990). Association of Official Analysis Chemists Official methods of analysis, Washington.

Azuara E, Beristan CI, Gutierrez GF (2002). Osmotic dehydration of apples by immersion in concentrated sucrose/maltodextrin solutions. Food Processing and Preservation, 26: 295-306.

Baughman DR, Liu YA (1995). Neural Networks in Bio-Processing and Chemical Engineering. Academic Press, New York.

Desai K, Surase SA, Saudagar PS, Lele SS, Singhal S (2008). Comparison of ANN and response surface methodology in fermentation media optimization. Case study of fermentative production of scleroglucan 41: 266-273.

Erenturk K, Erenturk S, Tabil LG (2004). A comparative study for the estimation of dynamical drying behavior of Echinacea angustifolia, regression analysis and neural network. Comput. Electronics Agric. 45 :71–90.

Erenturk K, Erenturk S (2007). Comparison of genetic algorithm and neural network approaches for drying process of carrot. J. Food Eng. 78: 905-912.

Hernandez-Perez JA, Garcia-Alvardo MA, Trystram G, Heyd B (2004). Neural networks for the heat and mass transfer prediction during drying of cassava and mango. Innov. Food Sci. Emerg. Technol. 5: 57-64.

Huang CY, Chen LH, Chen YL, Chang FM (2009). Evaluating the process of a genetic algorithm to improve the back propagation network. Monte Carlo Stud. 36:1459-1465.

Jang SR, Sun CT, Emizutani E (1997). Neuro-Fuzzy and Soft Computing: A computational approach to learning and machine intelligence, Prentice-Hall International, INC., USA.

Jiang N, Zhao Z, Reo L (2003). Design of structural modular neural networks with genetic algorithm. Adv. Eng. Software 34: 17-24.

Kerr WL, Kerdpiboon S, Devahastin S (2006). Neural network prediction of physical property changes of dried carrot as a function of fractal dimension and moisture content. Food Res. Int. 39: 1110–1118.

Ko YD, Moon P, Kim CE, Ham MH, Myonng JM, Yun I (2009). Modeling and optimization of the growth rate for the InO thin films using neural networks and genetic algorithms. Expert Syst. Appl. 36: 4061-4066.

Lisińska G, Leszczynski W (1989). Potato science and technology, London and New York, Elsevier applied science.

Maniezzq V (1994). Genetic evolution of the topology and weight distribution of neural network. IEEE Neural Networks. 5: 39-53.

Martynenko AI, Yang SX (2006). Biologically inspired neural computation of Ginseng drying rate. Biosyst. Eng. 95: 385-396.

Mohebbi A, Taheri M, Soltani A (2008). A neural network for predicting saturated liquid density using genetic algorithm for pure and mixed refrigerants. International Journal of Refrigeration, 31:1317–1327.

Movagharnejad K, Nikzad M (2007). Modeling of tomato drying using artificial neural network. Comput. Electronics Agric. 59:78–85.

Perrot N, Me L, Trystram G, Trichard JM, Decloux M (1998). Optimal control of the microfiltration of sugar product using a controller combining fuzzy and genetic approaches. Fuzzy Sets Syst. 94: 309-322.

Rastogi NK, Nayak CA, Raghavaro KS (2004). Influence of osmotic pretreatment on rehydration characteristics of carrots. J. Food Eng. 6: 287-292.

Samanta B, Al-Balushi KR, Al-Araimi SA (2003). Artificial neural network and support vector machine with GENETIC ALGORITHM for bearing fault detection. Eng. Appl. Artif. Intell. 16: 657-665.

Yao Z, Le Maguer M (1996). Mathematical modeling and simulation of mass transfer in osmotic dehydration processes. Part I: Conceptual and mathematical model. J. Food. Eng. 29: 349-360.