Contents lists available at ScienceDirect

Food and Bioproducts Processing

journal homepage: www.elsevier.com/locate/fbp

Prediction of moisture content in pre-osmosed and ultrasounded dried banana using genetic algorithm and neural network

M. Mohebbi, F. Shahidi, M. Fathi, A. Ehtiati, M. Noshad*

Department of Food Science and Technology, Ferdowsi University of Mashhad, PO Box 91775-1163, Iran

ABSTRACT

In this study, application of a versatile approach for estimation moisture content of dried banana using neural network and genetic algorithm has been presented. The banana samples were dehydrated using two non-thermal processes namely osmotic and ultrasound pretreatments, at different solution concentrations and dehydration times and were then subjected to air drying at 60 and 80 °C for 4, 5 and 6 h. The processing conditions were considered as inputs of neural network to predict final moisture content of banana. Network structure and learning parameters were optimized using genetic algorithm. It was found that the designed networks containing 7 and 10 neurons in first and second hidden layers, respectively, give the best fitting to experimental data. This configuration could predict moisture content of dried banana with correlation coefficient of 0.94. In addition, sensitivity analysis showed that the two most sensitive input variables towards such prediction were drying time and temperature.

Keywords: Banana; Genetic algorithm; Moisture content; Osmotic dehydration; Neural network; Ultrasound

1. Introduction

Banana (*Musa* spp.) is a significant source of carbohydrates, minerals and vitamin E (Wall, 2006). However, it is quite perishable due to its relatively high moisture content and degradable enzymes such as those accelerate non-enzymatic browning reactions (Fernandes et al., 2006). Drying is considered as a common preservation method due to dramatic reduction in enzymatic deterioration in results of moisture removal. Most common techniques for fruits dehydration are hot air drying. Nevertheless, this thermal process is a very energy-consuming operation and results in too much degradation of product quality (Nimmol et al., 2007). Combination of osmotic dehydration and ultrasound process can be applied as a non-thermal pretreatment for saving energy, ameliorating drying rate and minimizing product quality damage. Ultrasound power produces cavitations of bubbles, causes making microscopic channels, which leads to lower resistance to water diffusion and subsequently enhancing drying rate (García-Péreza et al., 2007). Fernandes et al. (2009) investigated the effect of ultrasound-assisted osmotic dehydration on pineapple mass transfer. Their results indicated that ultrasound application improves water diffusivity of pineapple. Jambrak et al. (2007) reported ultrasound treatment reduced drying time of mushrooms, Brussels sprouts and cauliflower and raised rehydration properties of these dried products.

Drying is a complicated process involving simultaneous heat and mass transfer (Yilbas et al., 2003). Physicochemical properties of dried products are usually forecasted by empirical models (Ceylan et al., 2007; De Temmerman et al., 2007; Garcia et al., 2007). However, the drawback of these models is that they are only capable of estimating data within the applied processing conditions.

An alternative approach to process dynamic modeling is the application of Artificial Neural Networks (ANNs). ANN is composed of adaptive non-linear simple processing elements called neurons or nodes equivalent to neurons in a biological system capable of performing parallel computations for data processing (Hertz et al., 1991). In recent years, ANN has been used as a useful tool to predict physical characteristics of dried or dehydrated products. Mohebbi et al. (2009) compared moisture estimation of dried shrimp using multiple linear

* Corresponding author. Tel.: +98 511 8795620; fax: +98 511 8787430.
E-mail address: mohebbat2000@yahoo.com (M. Mohebbi).
Received 17 February 2010; Received in revised form 14 July 2010; Accepted 2 August 2010
0960-3085/$ – see front matter
doi:10.1016/j.fbp.2010.08.001

regression (MLR) and Artificial Neural Network. Their results showed 0.80 and 0.86 coefficient of determination for MLR and ANN, respectively. Lertworasirikul and Tipsuwan (2008) employed multilayer feed-forward neural network to moisture content and water activity prediction of semi-finished cassava crackers during drying process. Their results showed that the best network composed of nine hidden neurons could estimate this parameter with high coefficient of determination ($R^2 = 0.9910$).

The selection of an appropriate neural network topology (i.e. number of hidden neurons, learning rate and momentum) which strongly affects predictability of network is critical and usually carried out by trial and error method. Genetic algorithm (GA) as an optimization technique can be used for overcoming this limitation of neural network. GA is inspired by the natural selection principles and Darwin's species evolution theory. GA offers several advantages over the conventional optimization method such as less susceptibility to be stuck at local minima, requiring little knowledge of the process being optimized and capability to find the optimum conditions when the search space is very large (Versace et al., 2004; Morimoto, 2006). Because of its robustness and easy customization for different kinds of optimization problems, GA has widely been applied in food engineering. Liu et al. (2007) optimized the neural network topology for estimating the moisture content of grain during the drying process using genetic algorithm and reported optimized network containing 6 neurons in hidden layer could accurately predict moisture content. Goñi et al. (2008) successfully used GA to obtain the initial training parameters of the neural network for prediction of freezing and thawing time.

The main intentions of this research were to use ultrasonication and osmotic dehydration as the non-thermal pretreatments before air drying and to develop a neural network model using genetic algorithm for moisture estimation of dried banana.

2. Materials and methods

2.1. *Sample preparation*

Fresh ripened banana was purchased from the local market and cut into 10 mm thickness slices. Average initial moisture content of banana was 75% (wet basis).

2.2. *Osmotic dehydration*

Banana slices were weighed and placed into a glass jar, which comprised osmotic solutions of sucrose (commercial sugar) and glucose (Merck Company). Slices were dehydrated with two different sugar concentrations (30 and 50° Brix) at temperature of 30 °C. The ratio of osmotic solution to sample was 6:1 (w/w) to avoid an excessive dilution of osmotic solution. Osmotic dehydration was performed under the same constant magnetic agitation to maintain a uniform temperature and concentration throughout the experiment. The samples were removed from the osmotic solutions after 30, 45 and 60 min and blotted with adsorbent paper to remove the excess solution.

2.3. *Ultrasound pretreatment*

Ultrasound pretreatment was carried out with the same conditions applied for osmotic dehydration while the samples were ultrasonicated for 10, 20 or 30 min. The experiments were performed in an ultrasonic bath (SCHAPER model Unique USC 25 kHz) without mechanical agitation at temperature of 30 °C. The ultrasound frequency and the intensity were 25 kHz and 500 W/m^2, respectively while the sonic power was 100 percent. The increase in temperature of solution during the experiments was lower than 3 °C after 30 min of ultrasonication.

2.4. *Air drying*

Hot air drying was performed in a laboratory drier (Soroush Medical Company) operating with air-velocity of 1.5 m/s. Before each drying experiment, the drier was run without sample for about 0.5 h to set desired conditions. The banana samples pretreated with either osmotic solution or ultrasound wave were subjected to air drying at 60 and 80 °C. Air drying was carried out for 4, 5 and 6 h. Finally, the moisture content of dried banana was determined (at 90 °C until constant weight was obtained). The experiments were conducted with 4 replications.

2.5. *Artificial Neural Network*

A multilayer feed-forward neural network, which is widely, used ANN consisting three layers namely input, output and hidden layer. Neurons in input layer simply direct input data to the neurons of hidden layer without any processing. The processing in hidden and output layers consists of collecting the data from previous layer, multiplying them by their corresponding weights, summing the values, putting the results in a non-linear or linear activation function (*f*) and finally adding a constant value called bias, Mathematically:

$$y_j = \sum_{i=1}^{n} f(w_{ij} x_i) + b_j \quad (1)$$

where x and y are input and output of neuron, respectively, n is number of inputs to the neuron, w_{ij} is the weight of the connection between neuron i and neuron j and b_j is the bias associated with jth neuron.

In this work, the ANN was first trained using single hidden layer. However, the results of this configuration for moisture content prediction were not satisfied; therefore, a neural network with four layers was applied. A hyperbolic tangent activation function (Eq. (2)) which is most popular function was used in first and second hidden layers, while a linear function was applied in the output layer. The number of hidden neurons varied from 1 to 25:

$$\tanh(x) = \frac{e^x - c_{-x}}{e^x + e^{-x}} \quad (2)$$

The input layer consists of six neurons (type of pretreatment, solution concentration, time of pretreatment, type of sugar, drying temperature and drying time), and the output layer contains one neuron (moisture content).

Totally, 144 data were experimentally collected and were randomly divided into three groups: training (40%), validating (30%) and testing data (30%). The first partition was used to perform the training of the network. The second one was applied to evaluate the quality of the network during the training and the last partition was used for estimating the performance of the trained network on new data, which never was seen by the network during the training.

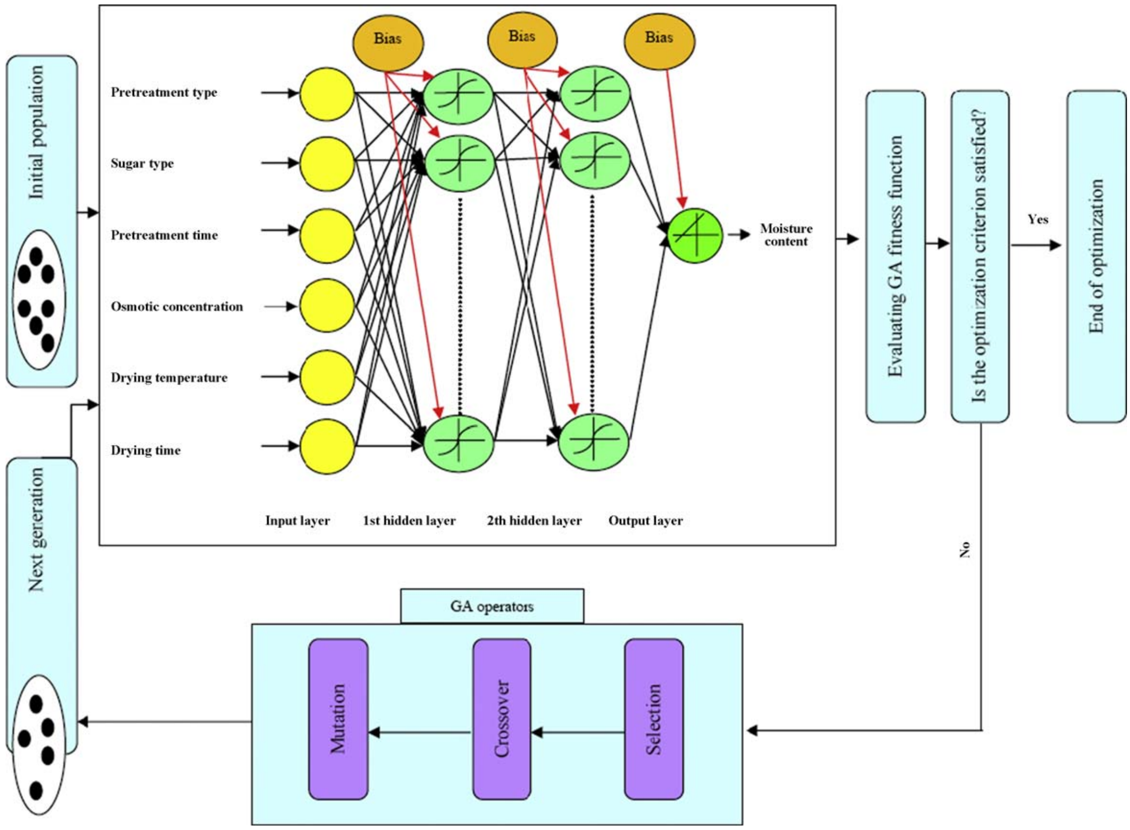

Fig. 1 – Schematic of optimization procedure of neural network using genetic algorithm.

Back-propagation algorithm with the momentum-learning rule 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. In this algorithm, training starts with randomly initialized connection weights. The response to each neuron in the output layer is then calculated and is compared with a corresponding desired output. Errors associated with the output neurons are propagated from output layer to the input layer through the hidden layers to modify the weights. Different statistical parameters namely mean-squared error (MSE), normalized mean-squared error (NMSE), mean absolute error (MAE) and correlation coefficient (R) were calculated based on testing data and were applied to compare the performance of different ANN architectures in prediction moisture content of dried banana. The mathematical equations of these statistical terms were presented by Fathi et al. (2009). Sensitivity analysis has been performed to identify the sensitive input variables against the moisture content. The sensitivity analysis was carried out by batch testing on the optimized network initiated by varying the first input between the mean $\pm$ one standard deviation, while all other inputs were fixed at their respective means. The network output was computed for 50 steps above and below the mean. This process was then iterated for each input. Finally, the standard deviation of output with respect to the variation of each input was calculated and, the values were used to identify the most important input, which affected the moisture content.

2.6. Genetic algorithm

The genetic algorithm is a global search algorithm, which is designed to mimic the principles of biological evolution in natural genetic system. The principles of GA are based on natural competitions of beings for appropriating limited natural sources. Superiority of winner beings is due to their individual characteristics that normally depend on their genes. Reproduction of superior beings causes to spread their genes. By successive selection of superior individuals and reproducing them, the population will be led to obtain more natural sources. The GA simulates this process and calculates the optimum of objective functions. The mathematical chromosomes could be operated upon by quasi-genetic operations of selection, crossover and mutation (Fig. 1). A selection operator evaluates the population according to fitness function and chooses the best individuals. After the selection, in crossover step, two individuals are chosen randomly and are reproduced into two new individuals. The mutation operation consists of randomly altering the value of each element of the chromosome according to the mutation probability. Mutation enhances the GA ability by intermittently injecting a random point in order to better search the entire parameter space, which allows the GA to possibly escape from local optima. These three operations are repeated until desired convergence on optimal or near-optimal of the solutions is achieved (Morimoto, 2006).

Choosing the appropriate values of learning rate and momentum has the strong effect on the prediction accuracy of ANN. Learning rate is the parameter that affects the rate of convergence of the network. Using too small value causes a long training time and applying too large learning rate may result in the training not being convergent. The momentum rate is used to improve convergence of ANN by avoiding getting stuck into local minima. In this study, neural network structure and training parameters were represented by haploid chromosomes consisting of "genes" of binary numbers. Each chromosome had three genes. The first gene represents the number of neurons in the hidden layers of the network,

Table 1 – Summery of optimized network architecture using genetic algorithm.

	First hidden layer			Second hidden layer			Output layer	
	Number of neurons	Learning rate	Momentum	Number of neurons	Learning rate	Momentum	Learning rate	Momentum
Network information	7	0.6357	0.3470	10	0.3952	0.5685	0.1932	0.0603

which could range from 1 to 25 neurons. The second and third genes depict the learning rate and momentum with which the network was trained. An initial population of 60 chromosomes was randomly generated. According to the literature (Heckerling et al., 2004; Izadifar and Zolghadri Jahromi, 2007; Mohebbi et al., 2008) the best generation number is set of 50. Therefore, the termination criterion of 60 was chosen. The roulette wheel selection based on ranking algorithm was applied for the selection operator. Uniform crossover and mutation operators with mixing ratio of 0.5 were used and the probabilities of the crossover and mutation operators were adjusted at 0.9 and 0.01, respectively. In this work, the ANN modeling and GA optimization were performed by Neurosolution for Excel software release 5.0, produced by NeuroDimension, Inc.

3. Results and discussion

Neural networks with 2–25 neurons and learning rate and momentum values ranging from 0 to 1 were trained using GA to achieve the optimal network configuration and learning parameters. Number of hidden neurons and learning rate and momentum values for optimized neural networks were tabulated in Table 1. The designed network has MSE, NMSE and MAE of 11.8799, 0.11889 and 2.3001, respectively. The best fitness attained during each generation of the optimization, is illustrated in Fig. 2. The best fitness, which is lowest the MSE value calculated across all the networks within the corresponding generation, is decreased crosswise generations until it becomes relatively constant after 6 generations. The matrices of weights (F matrix of 6×7 between input and first hidden layer, G matrix of 7×10 between first and second hidden layer and H matrix of 10×1 between second hidden layer and output layer) and bias values (B_{1th} matrix of 7×1 for first hidden layer, B_{2th} matrix of 10×1 for second hidden layer and B_{out} matrix of 1×1 for output layer) of optimized network are

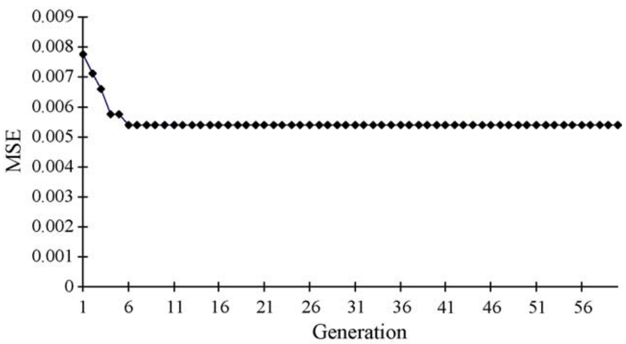

Fig. 2 – Best fitness (lowest MSE) versus generation of optimal neural network.

$$F = \begin{bmatrix} 0.358 & -0.286 & -0.238 & -0.008 & -0.104 & 0.010 & 0.086 \\ 0.258 & 0.110 & 0.223 & 0.145 & 0.230 & 0.364 & 0.424 \\ -0.338 & -0.255 & 0.163 & 0.355 & 0.182 & -0.297 & -0.013 \\ 0.383 & -0.171 & 0.121 & -0.291 & -0.276 & -0.513 & -0.016 \\ 0.340 & 0.071 & 0.221 & 0.045 & -0.754 & -0.177 & -0.418 \\ 0.310 & -0.451 & 0.437 & 0.222 & -0.190 & -0.319 & 0.123 \end{bmatrix}$$

$$G = \begin{bmatrix} 0.099 & -0.320 & 0.001 & 0.385 & -0.086 & -0.264 & 0.419 & -0.091 & 0.066 & 0.127 \\ -0.056 & -0.116 & -0.373 & 0.263 & -0.049 & -0.107 & -0.252 & 0.191 & 0.195 & 0.322 \\ 0.283 & -0.110 & 0.209 & 0.176 & 0.203 & -0.180 & -0.099 & -0.221 & -0.327 & -0.436 \\ 0.073 & 0.277 & 0.149 & 0.094 & -0.135 & -0.257 & -0.453 & -0.382 & 0.281 & 0.301 \\ -0.393 & 0.255 & -0.299 & -0.426 & -0.526 & -0.151 & 0.107 & -0.074 & -0.329 & 0.071 \\ 0.482 & -0.108 & 0.007 & 0.406 & -0.391 & 0.394 & 0.141 & -0.147 & 0.284 & 0.107 \\ -0.428 & 0.303 & 0.398 & -0.443 & -0.050 & 0.245 & -0.168 & -0.142 & 0.294 & -0.094 \end{bmatrix}$$

$$H = \begin{bmatrix} -0.405 \\ 0.297 \\ -0.447 \\ -0.393 \\ -0.422 \\ -0.033 \\ 0.493 \\ 0.3537 \\ 0.431 \\ -0.133 \end{bmatrix}$$

$$B_{1th} = \begin{bmatrix} -0.471 \\ -0.068 \\ -0.211 \\ 0.466 \\ -0.268 \\ 0.094 \\ 0.380 \end{bmatrix}; \quad B_{2th} = \begin{bmatrix} -0.288 \\ -0.135 \\ 0.430 \\ 0.196 \\ -0.100 \\ -0.275 \\ 0.140 \\ -0.500 \\ 0.364 \\ -0.009 \end{bmatrix}; \quad B_{out} = [0.079]$$

where the values in columns of matrix of F representing the weights of the connections between hidden neurons and type of pretreatment, type of sugar, time of pretreatment, solution concentration, drying temperature and drying time neurons in input layer, respectively.

Sensitivity of each variable in the proposed model is shown in Fig. 3. Among the input variables, drying time and tem-

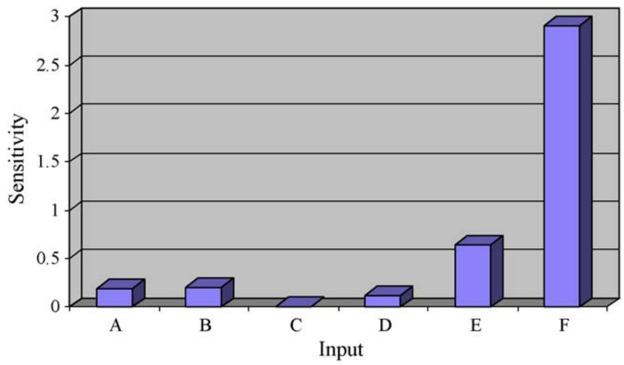

Fig. 3 – Sensitivity analysis on the optimized neural network (A, type of pretreatment; B, type of sugar; C, pretreatment time; D, sugar concentration; E, drying temperature; F, drying time).

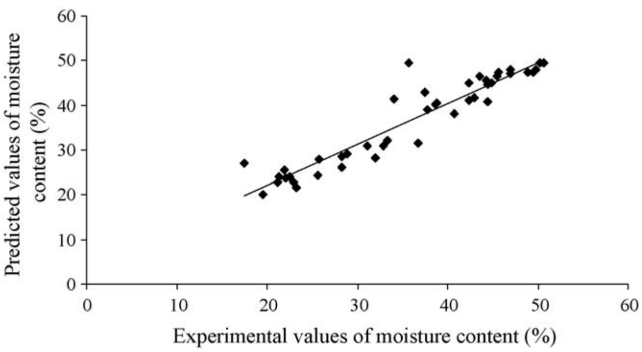

Fig. 4 – Actual versus predicted moisture content using optimal ANN ($R = 0.94$).

perature were most sensitive compared to other variables, which showing mostly these two parameters were important to the changes of moisture content of dried banana. These results could be attributed to the fact that the most of moisture removal was occurred during the hot air drying process. In spite of not having significant effect on moisture content, applying ultrasonication and osmotic pretreatments is strongly recommended due to improve drying efficiency and product quality. The performance of optimized ANN model with 7 and 10 neurons in first and second hidden layers for estimation of moisture content of dried banana based on test data that never was used for training was investigated and the results were plotted in Fig. 4. This figure reveals that the ANN estimated values of moisture content closely fitted with the experimental data ($R = 0.94$) and showing high ability of designed genetic-neural network model for moisture content prediction of dried banana.

4. Conclusions

In this study, the possibility of application of genetic-neural network model to forecast moisture content of dried banana pretreated using osmotic dehydration and ultrasound waves were investigated. The optimal model had 7 and 10 neurons in first and second hidden layers, respectively. This configuration had MSE, NMSE and MAE of 11.8799, 0.11889 and 2.3001, respectively. Having correlation coefficient of 0.94, the proposed neural network architecture, denoting superior ability of this intelligent model for on-line prediction of moisture content of dried banana.

References

Ceylan, I., Aktaş, M., Doğan, H., 2007. Mathematical modeling of drying characteristics of tropical fruits. Appl. Therm. Eng. 27, 1931–1936.

De Temmerman, J., Verboven, P., Nicolar, B., Ramon, H., 2007. Modelling of transient moisture concentration of semolina pasta during air drying. J. Food Eng. 80, 892–903.

Fathi, M., Mohebbi, M., Razavi, S.M.A., 2009. Application of image analysis and artificial neural network to predict mass transfer kinetics and color changes of osmotically dehydrated kiwifruit. Food Bioprocess. Technol., doi:10.1007/s11947-009-0222-y.

Fernandes, F.A.N., Gallão, M.I., Rodrigues, S., 2009. Effect of osmosis and ultrasound on pineapple cell tissue structure during dehydration. J. Food Eng. 90, 186–190.

Fernandes, F.A.N., Rodriguesb, S., Gasparetoc, O.C.P., Oliveira, E.L., 2006. Optimization of osmotic dehydration of bananas followed by air-drying. J. Food Eng. 77, 188–193.

Garcia, C.C., Mauro, M.A., Kimura, M., 2007. Kinetics of osmotic dehydration and air-drying of pumpkins (*Cucurbita moschata*). J. Food Eng. 82, 284–291.

García-Péreza, J.V., Cárcela, J.A., Beneditoa, J., Mulet, A., 2007. Power ultrasound mass transfer enhancement in food drying. Food Bioprod. Process. 85, 247–254.

Goñi, S.M., Oddone, S., Segura, J.A., Mascheroni, R.H., Salvadori, V.O., 2008. Prediction of foods freezing and thawing times: artificial neural networks and genetic algorithm approach. J. Food Eng. 84, 164–178.

Heckerling, P.S., Gerber, B.S., Tape, T.G., Wigton, R.S., 2004. Use of genetic algorithms for neural networks to predict community-acquired pneumonia. Artif. Intell. Med. 30, 71–84.

Hertz, J., Krogh, A., Palmer, R.G., 1991. Introduction to the Theory of Neural Computation. Addison-Wesley.

Izadifar, M., Zolghadri Jahromi, M., 2007. Application of genetic algorithm for optimization of vegetable oil hydrogenation process. J. Food Eng. 78, 1–8.

Jambrak, A.R., Mason, T.J., Paniwnyk, L., Lelas, V., 2007. Accelerated drying of button mushrooms, Brussels sprouts and cauliflower by applying power ultrasound and its rehydration properties. J. Food Eng. 81, 88–97.

Lertworasirikul, S., Tipsuwan, Y., 2008. Moisture content and water activity prediction of semi-finished cassava crackers from drying process with artificial neural network. J. Food Eng. 84, 65–74.

Liu, X., Chen, X., Wu, W., Peng, G., 2007. A neural network for predicting moisture content of grain drying process using genetic algorithm. Food Control 18, 928–933.

Mohebbi, A., Taheri, M., Soltani, A., 2008. A neural network for predicting saturated liquid density using genetic algorithm for pure and mixed refrigerants. Int. J. Refrig. 31, 1317–1327.

Mohebbi, M., Akbarzadeh-T, M.R., Shahidi, F., Mousavi, M., Ghoddusi, H.B., 2009. Computer vision systems (CVS) for moisture content estimation in dehydrated shrimp. Comput. Electron. Agric. 69, 128–134.

Morimoto, T., 2006. Genetic algorithm. In: Sablani, S.S., Rahman, M.S., Datta, A.K., Mujumdar, A.S. (Eds.), Food and Bioprocess Modeling Techniques. CRC Press, New York.

Nimmol, C., Devahastin, S., Swasdisevi, T., Soponronnarit, S., 2007. Drying and heat transfer behavior of banana undergoing combined low-pressure superheated steam and far-infrared radiation drying. Appl. Therm. Eng. 27, 2483–2494.

Versace, M., Bhatt, R., Hinds, O., Shiffer, M., 2004. Predicting the exchange traded fund DIA with a combination of genetic algorithms and neural networks. Expert. Syst. Appl. 27, 417–425.

Wall, M.M., 2006. Ascorbic acid, vitamin A, and mineral composition of banana (*Musa* sp.) and papaya (*Carica papaya*) cultivars grown in Hawaii. J. Food Compos. Anal. 19, 434–445.

Yilbas, B.S., Hussain, M.M., Dincer, I., 2003. Heat and moisture diffusion in slab products to convective boundary condition. Heat Mass Transfer 39, 471–476.