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Comparison between artificial neural network (multi-layer perceptron) and mathematical Peleg's model for moisture content estimation of dried potato cubes

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RESEARCH PAPER

Abstract

In this study an artificial neural network, multi-layer perceptron (MLP), and Peleg's mathematical model were used to find the best model for the prediction of rehydration kinetic of air dried potato cubes. For rehydration, samples were immersed in water during different periods of time and temperatures (23±2 °C and 100±2 °C). Rehydration kinetic was monitored by measuring samples weights at regular intervals. In MLP neural network, water temperature, soaking time and potato varieties (Agria, Satina and Kenebek) were used as input parameters and the moisture content was used as output parameter. The results were compared with experimental data. Both Peleg's model and MLP had a proper correlation coefficient for each variety and water temperature but the correlation coefficient of the generalized Peleg's model was lower than of MLP.

Keywords: artificial neural network, Peleg's model, potato cubes, rehydration

1. Introduction

Water elimination is a suitable way to protect foods from spoilage. Indeed, the lack of water prevents foods from the microorganisms' development. In these conditions, little enzymatic activity is possible and the major part of chemical reactions is slowed down (Tortoe *et al.*, 2007). In order to improve protection, practically all water quantity in foods must be carried away.

Potato is one of the most important agricultural crops and there is remarkable loss of this produce because of unfavourable storage conditions. Therefore, it is useful to convert raw potatoes into some processed products such as dried ones. Conventional air-drying is the most frequently used dehydration operation in food and chemical industry.

In this case, drying kinetics is greatly affected by air temperature and material characteristic dimension, while all other process factors exert practically negligible influence (Kiranoudis *et al.*, 1997). In air drying of foods, together with the partial evaporation of the product's water content, some physical and chemical changes in the tissue structure occur (Lewicki, 1998). Shrinkage, porosity decrease and changes in physical properties such as texture, are some of the alterations that may occur during drying (Lewicki and Jakubczyk, 2004; Maskan, 2001).

Most of the dehydrated products are usually rehydrated during their use. Mathematical models of dehydration and rehydration operations are important in the design and optimization of those operations (Berin and Blazquez, 1986; Vagenas and Marinos-Kouris, 1991). It chiefly involves determination of drying and rehydration kinetics, which describe the mechanisms and the influence that certain process variables exert upon moisture transfer (Gekas and Lamberg, 1991). In typical industrial applications, kinetic models are often empirical equations involving parameters which are functions of the main process variables.

Many theoretical, empirical and semi-empirical models have been employed for modelling the water absorption behavior of agricultural products during soaking. Theoretical models allow us to relate the experimental results with physical laws. The theoretical mechanisms for the kinetics of the diffusion process have been proposed, from the simplest, Fickian diffusion to other, more complex ones, of the non-Fickian diffusion (Dhakal *et al.*, 2007; Vogt *et al.*, 2004).

Peleg (1988) proposed an empirical model to describe the water absorption kinetics during rehydration which has been successfully applied to different products such as chestnut (Moreira *et al.*, 2008), apple (Bilbao- Sáinz *et al.*, 2005) and potato (Cunningham and McMinn, 2007).

Some simple first order kinetic models can describe the moisture transfer during rehydration too (Krokida and Marinos-Kouris, 2003; Markowski *et al.*, 2009; Piergiovanni, 2011; Sopade *et al.*, 2007).

Artificial neural network (ANN) is a mathematical tool, which tries to represent low-level intelligence in natural organisms and it is a flexible structure, capable of making a non-linear mapping between input and output spaces (Rumelhart *et al.*, 1986).

The multi-layer perceptron (MLP) network (Figure 1), sometimes called back propagation network, is probably the most popular ANN in engineering problems in the case of non-linear mapping and is called 'universal approximator'. It consists of an input layer, a hidden layer and an output layer. The input nodes receive the data values and pass them on to the first hidden layer nodes. Each one collects the input from all input nodes after multiplying each input value by a weight, attaches a bias to this sum, and passes on the results through a non-linear transformation like the sigmoid transfer function. This forms the input either for the second hidden layer or the output layer that operates identically to the hidden layer. The resulting transformed output from each output node is the network output. The

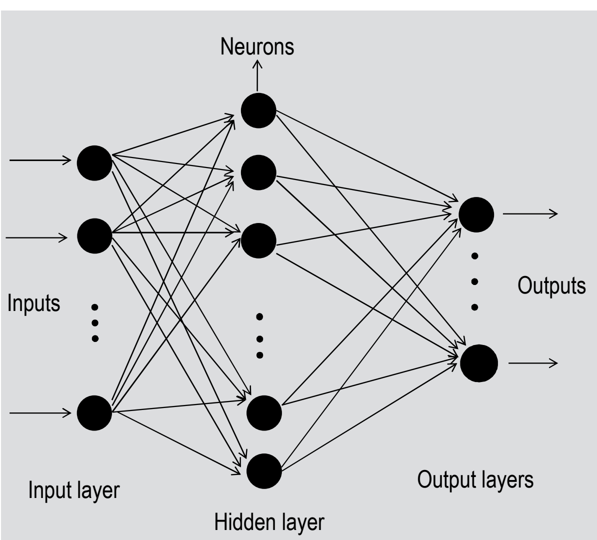

Figure 1. The multi-layer perceptron neural network.

network needs to be trained using a training algorithm such as back propagation, cascade correlation and conjugate gradient. Basically the objective of training patterns is to reduce the global error. The goal of every training algorithm is to reduce this global error by adjusting the weights and biases.

Artificial neural networks have already been applied to simulate processes such as fermentation (Latrille *et al.*, 1993), cross flow microfiltration (Dornier *et al.*, 1995), drying behaviour of different food and agricultural materials such as carrot (Erenturk and Erenturk, 2007; Kerdpiboon *et al.*, 2006), tomato (Movagharnejad and Nikzad, 2007), ginseng (Martynenko and Yang, 2006), cassava and mango (Hernandez-Perez *et al.*, 2004) and osmotic dehydration (Trelea *et al.*, 1997), but there is few information about application of artificial neural networks in simulation of soaking processes (in particular for grain).

This study was carried out to test and validate the efficiency of ANN for simulating the soaking behaviour and the effect of temperature and time on the rehydration of potato cubes. The results were also compared with those obtained from Peleg's model and from a simple first order kinetic model.

2. Materials and methods

Materials

Three potato cultivars (Agria, Satina and Kenebek) were supplied by the agricultural centre of Gorgan (Iran). Initial moisture contents were 82.05, 82.28 and 81.405%, respectively. Potatoes were peeled and cut to 1×1×1 cm cubes. To inhibit browning, samples were blanched in hot water (97±2 °C) for three min.

Drying treatments

To dry samples, a hot air oven (Memmert WB14, Memmert GmbH, Köln, Germany) was used and samples were dried in 65 °C in an air velocity of 2 m/s to reach to 6% moisture content (wet basis). Some of the dried samples were packed in polyethylene bags and stored in room temperature (25±2 °C). Vacuum of packages was 30%, their thickness was 1 mm and there was not any permeability of water and moisture.

Rehydration

The dried potato samples were then rehydrated by immersing in distilled water at a thermostatically controlled temperature (Cunningham and McMinn, 2007). At specified time intervals, the samples were removed, blotted with tissue paper to remove superficial water and weighed. Soaking times to reach constant weight of samples were recorded in time intervals ranging from 10 min at the beginning of the rehydration process to 30 min towards the end of water absorption at water temperature of 23±2 °C and 10 sec at 100±2 °C (Cunningham and McMinn, 2007). No correction was made for lost solids, as the quantity of absorbed water was much greater than the quantity of solids leached (Maskan, 2001). Each experiment was performed in triplicate.

Mathematical modelling

For mathematical modelling of the variation of either moisture content or moisture ratio of potato cubes during soaking at each temperature, the Peleg's model and multi-layer perceptron ANN were tested. The performances of the models were compared according to their coefficient of determination (R2) and mean square error (MSE) of either moisture content or moisture ratio (Resio *et al.*, 2003).

Peleg's model

Peleg (1988) proposed an empirical model to describe the water absorption kinetics during rehydration, which is given by:

$$X = X_i + \frac{t}{K_1 + K_2 \times t} \tag{1}$$

Where X is the moisture content at time t, X_i is the initial moisture content, K_1, the Peleg's rate constant, is a kinetic parameter and K_2 is another parameter related to the equilibrium moisture content, X_{eq}. When $t \to \infty$, the equilibrium moisture content can be calculated by:

$$X_{eq} = X_i + \frac{1}{K_2} \tag{2}$$

Equation 1 can be linearized:

$$\frac{t}{X - X_i} = K_1 + K_2 \times t \tag{3}$$

Training the artificial neural network

Experimental data from this study were used to train and test multi-layer perceptron ANN for prediction of potato cubes moisture content during the soaking process. Totally, 215 data were collected for two different soaking temperatures of 23±2 and 100±2 °C and three potato variety which 60% of them (include of maximums and minimums) were used as train data for learning process and 40% were used as test data for calibrating and verification.

The number of neurons in input and output layers depends on independent and dependent variables, respectively. Moisture content was considered as dependent variable and soaking temperature, time and variety were selected as independent variables. Therefore, one and three neurons were devoted to output and input layers, respectively. The number of neurons in the hidden layer and the parameter α were determined by calibration through several run tests. In this study one hidden layer including 8, 10, 12, 17, 20, 25 and 30 neurons were used for the MLP neural networks. Various activation functions were tested for MLP neural networks and the sigmoid function presented the best results.

3. Results and discussion

Peleg's model

Parameters of Peleg's model were calculated according to Equation 1. In order to do this, Equation 1 was linearized as has been shown in Equation 3. Results are shown in Table 1.

The Peleg's rate constant (K_1), decreased with increase of temperature, which shows that water transfer (related to the inverse of K_1) is promoted by increase of temperature. After drying, shrinkage and hardness of samples delayed water penetration and samples needed to be immersed for longer time in 100 °C water. This caused some damages in structure and texture of cubes and their water capacity decreased, so K_2, which is the capacity constant of Peleg's model, increased with temperature (Salimi *et al.*, 2010).

Some authors indicate that the K_2 value can change if structure or other properties are modified by temperature during rehydration (García-Pascual *et al.*, 2005; Lopez *et al.*, 1995). In this manner, the K_2 parameter increases with temperature during rehydration of chickpea (Turhan *et al.*, 2002) and carrot (Planinic *et al.*, 2005).

Multi-layer perceptron artificial neural networks

In order to obtain a desired answer, multi-layer perceptron was utilized. When the error between desired and predicted values is minimum, training process meets the stability. The increasing method was used for selection of neurons. By this method, when the network is trapped into the local minimum, new neurons are gradually added to the

Table 1. Parameters of Peleg's model.

Potato variety	Water temperature	X_{eq}[1]	K_1[2]	K_2[3]
Agria	23 °C	3.002	23.326	0.340
Satina	23 °C	3.064	15.903	0.350
Kenebek	23 °C	3.080	17.200	0.331
Agria	100 °C	2.076	0.466	0.496
Satina	100 °C	2.004	0.579	0.515
Kenebek	100 °C	2.541	0.480	0.403

[1] Equilibrium moisture content.
[2] Peleg's rate constant.
[3] Peleg's capacity constant.

network. This method has more practical potential to detect the optimum size of the network. The increasing method has some advantages which are: (a) the network complexity gradually increases with increasing neurons; (b) the optimum size of the network always obtains by adjustments; and (c) monitoring and evaluation of local minimum carry out during the training process. Various threshold functions were used to reach the optimized status (Amiri Ghayjan and Esna-Ashari, 2010; Demuth and Beale, 2003), but it should be noted that there are two basic commonly used sigmoidal activation functions which are the logistic sigmoid (LOGSIG) and the tangental sigmoid (TANSIG), which is derived from the hyperbolic tangent and has the advantage over the LOGSIG of being able to deal directly with negative numbers:

$$Y_j = \frac{1}{1+\exp(-X_j)} \qquad \text{(LOGSIG)} \tag{4}$$

$$Y_j = \frac{2}{(1+\exp(-2X_j))-1} \qquad \text{(TANSIG)} \tag{5}$$

Where X is the independent variable and Y is the dependent variable in the functions.

As is shown in Table 2, the best results for MLP network with the Levenberg-Marquardt algorithm in the first strategy belonged to TANSIG threshold function with one hidden layer and 10 neurons. This composition produced MSE=0.0001%, R2=0.987 converged in 54 epochs. MSE for training and testing patterns is shown in Figure 2.

Table 2. Levenberg-Marquardt algorithm for different neurons and threshold functions in a multi-layer perceptron.

Threshold function	Number of neurons	MSE[1] (%)	R2[2]	Epochs
tangental sigmoid	8	0.0005	0.945	38
	10	0.0001	0987	54
	12	0.0004	0.955	34
	17	0.0021	0.799	76
	20	0.0007	0.639	16
	25	0.0008	0.917	38
	30	0.0012	0.886	13
logistic sigmoid	8	0.0021	0.759	174
	10	0.0003	0.961	112
	12	0.0010	0.888	220
	17	0.0002	0.973	52
	20	0.0012	0.876	25
	25	0.0023	0.760	33
	30	0.0006	0.943	65

[1] Mean square error.
[2] Coefficient of determination.

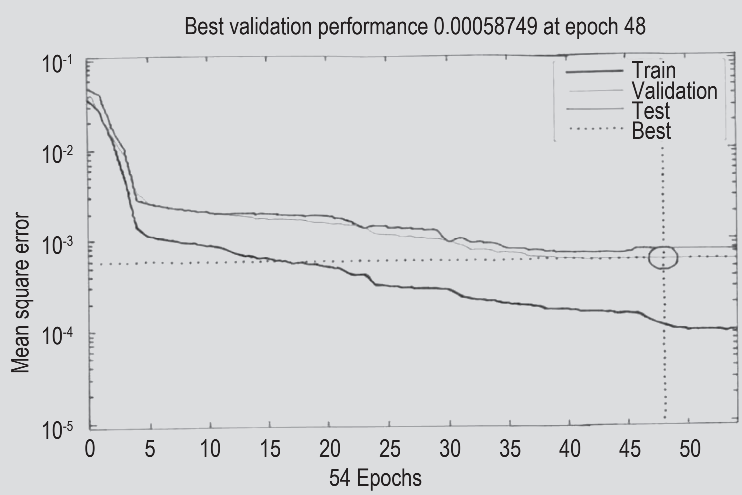

Figure 2. Mean square error of training and testing patterns for the best artificial neural network.

Comparison between a mathematical model and MLP can be observed by statistical parameters as MSE and R2. Also some other parameters such as average of proportion of calculated moisture contents to measured ones can be used to find out which models are more suitable. The proportions which are nearer to one show less dispersion between measured and calculated data (Table 3).

Moisture content predicted with the generalized Peleg's model and MLP network were compared to the observed moisture content in Figures 3 and 4. In these figures the dotted lines represent the 0.95 and 1.05 measured data. These results demonstrate that the agreement is very good in MLP neural network and this model tracks the observed moisture contents well throughout the various conditions.

Models (generalized Page's model and MLP network) were compared based on R2, MSE, the average of the proportion of calculated moisture contents to the measured ones, and the standard deviation of the proportion of calculated moisture contents to the measured ones. The results are shown in Table 4.

Table 4. Statistical results obtained for the generalized Peleg's model and multi-layer perceptron (MLP).

Model	R2[1]	MSE[2] (%)	Average[3]	STDEV[4]
Generalized Peleg's model	0.832	0.001	0.99	0.1
MLP	0.987	0.0001	0.99	0.06

[1] Coefficient of determination.
[2] Mean square error.
[3] Average of the proportion of calculated moisture contents to the measured ones.
[4] Standard deviation of the proportion of calculated moisture contents compared to the measured contents.

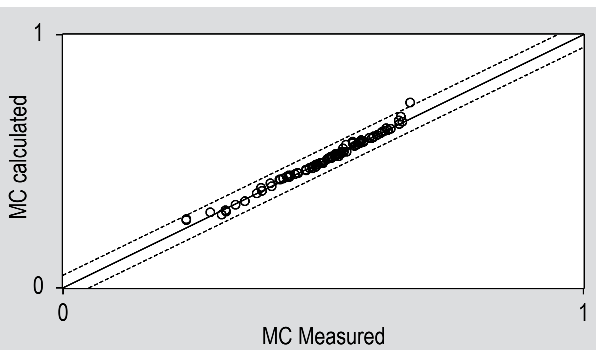

Figure 3. Comparison between measured and calculated values of moisture content (MC) by multi-layer perceptron neural network model.

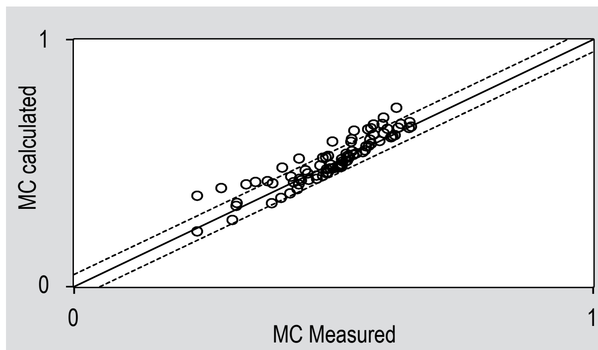

Figure 4. Comparison between measured and calculated values of moisture content (MC) by generalized Peleg's model.

Table 3. Statistical results obtained for Peleg's model and multi-layer perceptron (MLP).

Potato variety	Water temperature	Model	R2[1]	MSE[2] (%)	Average[3]	STDEV[4]
Agria	23 °C	Peleg	0.990	0.01	0.97	0.11
Satina	23 °C	Peleg	0.991	0.009	0.98	0.08
Kenebek	23 °C	Peleg	0.993	0.007	0.98	0.09
Agria	100 °C	Peleg	0.994	0.001	0.99	0.03
Satina	100 °C	Peleg	0.988	0.003	0.99	0.05
Kenebek	100 °C	Peleg	0.988	0.005	0.99	0.05
Agria, Satina and Kenebek		MLP	0.987	0.0001	0.99	0.06

[1] Coefficient of determination.
[2] Mean square error.
[3] Average of the proportion of calculated moisture contents to the measured ones.
[4] Standard deviation of the proportion of calculated moisture contents compared to the measured contents.

It is assumed that the model with the lowest MSE and the highest R2 is the best to describe rehydration behaviour (Kashaninejad *et al.*, 2009). Therefore, the suitable model to describe the soaking characteristics of potato cubes was found to be MLP neural network with one hidden layer, 10 neurons and TANSIG threshold function.

4. Conclusions

Based on this study it was concluded that Peleg's model had proper correlation coefficients for each variety and water temperature with underlining Agria variety in 100 °C (R2=0.994). However, the correlation coefficient of the generalized Peleg's model was significantly lower (0.832) in comparison to MLP.

The best correlation coefficient was observed by MLP ANN with one hidden layer, 10 neurons and TANSIG threshold function. In spite of the results of this article, yet more work is needed to show that the ANN model is useful in a wider context.

References

Amiri Ghayjan, R. and Esna-Ashari, M., 2010. Comparison between artificial neural networks and mathematical models for equilibrium moisture content estimation in raisin. Journal of Agricultural Engineering International 7: 1305-1311.

Berin, R. and Blazquez, M., 1986. Modeling and optimisation of a dryer. Journal of Drying Technology 4: 45-66.

Bilbao-Sáinz, C., Andres, A. and Fito, P., 2005. Hydration kinetics of dried apples as affected by drying conditions. Journal of Food Engineering 68: 369-376.

Cunningham, S.E. and McMinn, W.A., 2007. Effect of processing conditions on the water absorption and texture kinetics of potato. Journal of Food Engineering 84: 214-223.

Demuth, H. and Beale, M., 2003. Neural network toolbox for Matlab-users guide version 4.1. Mathworks Inc., Natrick, NY, USA, 89 pp.

Dhakal, H.N., Zhang, Z.Y. and Richardson, M.O.W., 2007. Effect of water absorption on the mechanical properties of hemp fibre reinforced unsaturated polyester composites. Journal of Science and Technology: 67, 1674-1683.

Dornier, M., Decloux, M., Trystram, G. and Lebert, A., 1995. Dynamic modeling of crossflow microfiltration using neural networks. Journal of Membrane Science 98: 263-273.

Erenturk, S. and Erenturk, K., 2007. Comparison of genetic algorithm and neural network approaches for the drying process of carrot. Journal of Food Engineering: 78, 905-912.

García-Pascual, P., Sanjuán, N., Bon, J., Carreres, J.E. and Mulet, A., 2005. Rehydration process of *Boletus edulis* mushroom: characteristics and modeling. Journal of Food and Agriculture 85: 1397-1404.

Gekas, V. and Lamberg, I., 1991. Determination of diffusion coefficients in volume changing systems-application in the case of potato drying. Journal of Food Engineering 13: 317-326.

Hernandez-Perez, J.A., Garcia-Alvarado, M.A., Trystram, G. and Heyd, B., 2004. Neural networks for heat and mass transfer prediction during drying of cassava and mango. Innovative Food Science Emergency Technology 5: 57-64.

Kashaninejad, M., Dehghani, A.A. and Kashiri, M., 2009. Modeling of wheat soaking using two artificial neural networks (MLP and RBF). Journal of Food Engineering 91: 602-607.

Kerdpiboon, S., Kerr, W.L. and Devahastin, S., 2006. Neural network prediction of physical property changes of dried carrot as a function of fractal dimension and moisture content. Journal of Food Research International 39: 1110 1118.

Kiranoudis, C.T., Tsami, E., and Maroulis, Z.B., 1997. Microwave vacuum drying kinetics of some fruits. Drying Technology 15: 2421-2440.

Krokida, M.K. and Marinos-Kouris, D., 2003. Rehydration kinetics of dehydrated products. Journal of Food Engineering 57: 1-7.

Latrille, E., Corrieu, G. and Thibault, J., 1993. pH prediction and final fermentation time determination in lactic acid batch fermentations. Computer and Chemical Engineering 17: 423-428.

Lewicki, P.P., 1998. Effect of pre-drying treatment, drying and rehydration on plant tissue properties: a review. International Journal of Food Properties 1: 1-22.

Lewicki, P.P. and Jakubczyk, E., 2004. Effect of hot air temperature on mechanical properties of dried apples. Journal of Food Engineering 64: 307-314.

Lopez, A., Pique, M.T., Clop, M., Tasias, J., Romero, A., Boatella, J. and Garcia, J., 1995. The hygroscopic behavior of the hazelnut. Journal of Food Engineering 25: 197-208.

Markowski, M., Bondaruk, J. and Blaszezac, W., 2009. Rehydration behaviour of vacuum-microwave-dried potato cubes. Drying Technology 27: 296-305.

Martynenko, A.I. and Yang, S.X., 2006. Biologically inspired neural computation for ginseng drying rate. Journal of Biosystem Engineering 95: 385-396.

Maskan, M. 2001. Drying shrinkage and rehydration characteristics of kiwifruits during microwave drying. Journal of Food Engineering 48: 177-182.

Moreira, R., Chenlo, F., Chaguri, L. and Fernandes, C., 2008. Water absorption, texture and color kinetics of air-dried chestnuts during rehydration. Journal of Food Engineering 86: 584-594.

Movagharnejad, K. and Nikzad, M., 2007. Modeling of tomato drying using artificial neural network. Journal of Computers and Electronics in Agriculture 59: 78-85.

Peleg, M.A., 1988. empirical model for the description of moisture sorption curves. Journal of Food Science 53: 1216- 1219.

Piergiovanni, A.R., 2011. Kinetic of water adsorption in common bean: considerations on the suitability of Peleg's model for describing bean hydration. Journal of Food Processing and Preservation 35: 447-452.

Planinic, D., Velic, S.T., Bilic, M. and Bucic, A., 2005. Modelling of drying and rehydration of carrots using Peleg's model. Journal of European Food Research and Technology: 221, 446-451.

Resio, A.N.C., Aguerre, R.J. and Suarez, C., 2003. Study of some factor affecting water absorption by amaranth grain during soaking. Journal of Food Engineering 60: 391-396.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J., 1986. Learning internal representations by error propagation. In: Rumelhart, D.E. and McClelland, J.L. (eds.) Parallel distributed processing: explorations in the microstructure of cognition, volume 1: foundations. The MIT Press, Cambridge, MA, USA, pp. 318-362.

Salimi Hizaji, A., Maghsoudlou, Y. and Jafari, S.M., 2010. Application of Peleg model to study effect of water temperature and storage time on rehydration kinetics of air dried potato cubes. Latin American Applied Research 40: 131-136.

Sopade, P.A., Xun, P.Y., Halley, P.J. and Hardin, M., 2007. Equivalence of the Peleg, Pilosof and Singh-Kulshrestha models for water absorption in food. Journal of Food Engineering 78: 730-734.

Tortoe, C., Orchard, J. and Beezer, A., 2007. Osmotic dehydration kinetics of apple, banana and potato. International Journal of Food Science and Technology 42: 312-318.

Trelea, I.C., Raoult-Wack, A.L. and Trystram, G., 1997. Application of neural network modelling for the control of dewatering and impregnation soaking process (osmotic dehydration). Journal of Food Science and Technology International 3: 459-465.

Turhan, M., Sayar, S. and Gunasekaran, S., 2002. Application of Peleg model to study water absorption in chickpea during soaking. Journal of Food Engineering 53: 153-159.

Vagenas, G.K. and Marinos-Kouris, D., 1991. The design and optimisations of an industrial dryer for Sultana raisins. Journal of Drying Technology 9: 439-461.

Vogt, B.D., Soles, C.L., Lee, H.J., Lin, E.K. and Wu, W.L., 2004. Moisture absorption and absorption kinetics in polyelectrolyte films: influence of film thickness. Journal of Langmuir 20: 1453-1458.