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Prediction of ultrasonic osmotic dehydration properties of courgette by ANN

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RESEARCH ARTICLE

Abstract

In this research, ultrasound assisted osmotic dehydration of courgette rings using sorbitol/sucrose solution under different temperature (5, 25 and 50 °C for 2 h) was investigated. Sucrose (35%, w/v) and sorbitol solutions (5, 10 and 15%, w/v) were used for osmotic dehydration processes. The reliability of using an artificial neural network (ANN) approach for predicting the osmotic dehydration properties of courgette was investigated. Immersion time, type of treatment, osmotic solution temperature and concentration were selected as input variables and solid gain and water loss were chosen as the outputs of the network. Results showed that all processing factors had a significant effect on the solid gain and water loss ($P<0.01$). Increasing osmotic solution concentration and temperature lead to increases in water loss and solid gain for both samples of ultrasonicated and non-ultrasonicated treatments. The results of ANN indicated that, tanh activation function with 46 neurons in first and second hidden layers was selected as the best activation function. This network was able to predict solid gain and water loss with R^2 value equals to 0.938 and 0.985, respectively.

Keywords: courgette, mass transfer, osmotic dehydration, sorbitol/sucrose solution, ultrasound

1. Introduction

Courgette, (*Cucurbita pepo* L.), belongs to the family of the *Cucurbitaceae* (Izumi and Watada, 1995). It is a rich source of different vitamins (C, A, K and B) and minerals (Mn, Mg, K, Ca, Fe and Zn). It has abundant dietary fibre and omega 3 fatty acids. The dietary fibre present helps to lower blood cholesterol level, reducing the risk of heart diseases (Tavakolipour *et al.*, 2014). It is also used as a main part of many foods such as stews and soups. According to Food and Agriculture Organization statistics (http://faostat3.fao.org), Iran produced about 965,000 MT of gourd (approximately 4.67% of the world's production) in 2012. Like other fruit, due to high moisture content courgette is highly perishable and needs suitable preservation methods for increasing its shelf-life (Izumi and Watada, 1995). Drying is one of the oldest methods for food preservation, mainly because of moisture removal from the food reduces the rate of bacteria, yeast and mould growth (Mandala *et al.*, 2005). Osmotic dehydration processes have been widely used for preserving fruits and vegetables due to their potential for preserving sensory attributes and nutritional properties similar to fresh fruits and vegetables (Najafi *et al.*, 2014). Various osmotic agents have been used including glucose, fructose, lactose, dextrose, maltose, polysaccharides, maltodextrin, corn starch syrup, whey, sorbitol, ascorbic acid, citric acid, calcium chloride, and combinations of these osmotic agents (Rahman, 2007). Among these osmotic agents, sorbitol is a dietetic sugar and can be used as an alternative to replace sucrose and invert sugar in the final product. Therefore, the final product can be used as a dietary product for peoples with diabetes and heart diseases and chronic obesity (Todorova *et al.*, 1982).

Presently ultrasound is considered to be a promising technology in food dehydration process. When ultrasound waves are directly coupled to the foods, they produce a rapid series of alternative compressions and expansions reactions and a kind of sponge effect and so lead to the quick migration of moisture from the product (Gallego-Juarez *et al.*, 2007). This mechanism is responsible for drying and dehydrating foods. Cavitation leads to the formation of bubbles in the liquid, which can explosively collapse and generate localised pressure fluctuations. This effect increases the diffusion rate during osmotic processes and accelerates de-gassing of the tissue (Rahman, 2007; Sun, 2005). Ultrasonic-assisted osmotic dehydration can be carried out at lower solution temperatures to obtain a higher rate of water loss and solid gain whilst preserving the natural flavour, colour and heat-sensitive nutritional compounds and reduces energy consumption (Sun, 2005).

Several papers have addressed the requirement of non-thermal processing technologies such as ultrasound and osmotic dehydration. For example Raj *et al.* (2014) investigated Osmo-air dehydration of different Indian apricot (*Prunus armeniaca L.*) cultivars. The results revealed that among the different cultivars of apricot, cv. Kaisha followed by New Castle showed a better yield and quality of dried product. Rawson *et al.* (2011) studied the effect of ultrasound and blanching pre-treatments on polyacetylene and carotenoid content of hot air and freeze dried carrot slice. They showed that ultrasound pre-treatment can be used as an alternative to conventional blanching treatment in the drying of carrots. Additionally, Fernandes *et al.* (2009) studied the influence of ultrasound pre-treatment on pineapple cellular structure during dehydration. They stated that, ultrasound application increased sugar loss and water diffusivity because of the formation of microscopic channels, which offered lower resistance to water and sugar diffusion. Generally, the results of these researches illustrated that the use of ultrasound-assisted osmotic dehydration improved mass transfer rate during osmotic dehydration and it amended quality of final products.

Today, artificial neural networks (ANN) play an important role as a powerful tool in predicting the processing parameters in different food processing unit operation. For example Aghajani *et al.* (2012); Kashiri *et al.* (2012); Ghahfarrokhi *et al.* (2013); Mokhtarian *et al.* (2014a,b) used ANN methods for modelling drying processes of green malt, soaking process of sorghum, non-thermal inactivation of peroxidase enzyme, air drying and osmotic dehydration of pumpkin fruit, respectively. Momenzadeh *et al.* (2011) investigated drying behaviour of shelled corn dried in a microwave-assisted fluidised bed dryer using ANN. Lertworasirikul and Saetan (2010) used ANN modelling to predict mass transfer parameters of kaffir lime peel (i.e. water loss and solid gain). Goni *et al.* (2008) used an artificial neural approach to predict freezing and thawing times on foods. However, no research was observed in the context of the impact of ultrasound-Osmo-dehydration method on the physical parameters of courgette and prediction of this process using an ANN.

The purpose of this study was to investigate the ultrasonic osmotic dehydration of courgette and prediction of osmotic dehydration parameters using an ANN method.

2. Material and methods

Raw material preparation

Fresh courgette was purchased from a local market in Sabzevar, Iran. At the beginning of each experiment, the courgette was washed with fresh water to remove the courgette fines adhered to the fruit surface and cut into rings with a diameter of 20 mm and thickness of 5 mm. The initial weight of each courgette slice was about 2 g. The initial moisture content was determined by drying in hot air convective oven (model UNE 400 PA; Memmert, Scheabach, Germany) at 105 °C for 48 h (Mokhtarian *et al.*, 2014a).

Ultrasound-assisted osmotic dehydration process

In this study different osmotic solution concentration [sucrose 35% + sorbitol 5%, w/v (S_5), sucrose 35% + sorbitol 10%, w/v (S_{10}), sucrose 35% + sorbitol 15%, w/v (S_{15})] and different temperatures (5, 25 and 50 °C) were used. The experiments with ultrasound treatment were carried out in 250 ml beaker. The experiments were carried out by an ultrasonic probe system (model UP 200H with ultrasound frequency of 24 kHz; Hielscher Ultrasonics GmbH, Teltow, Germany). Courgette rings were immersed in an osmotic solution, then the probe (model S7/Micro Tip7; Hielscher Ultrasonics GmbH) was inserted into the sample beaker and continuous sound waves were delivered to the sample for 120 min. Treated samples were removed from the osmotic solutions and their surfaces washed out under distilled, deionised water and placed on Whatman filter paper (GE Healthcare Bio-Sciences, Pittsburgh, PA, USA) to absorb the excess surface water; subsequently, the samples were weighed. The osmotic solution temperature was adjusted using a water bath (model E200; Lauda, Lauda-Königshofen, Germany). In all experiments, in order to minimise the dilution effect of the osmotic solution during the dehydration process, the ratio of fruit to osmotic solution was kept constant at a ratio of 1 to 20 kg/l (Mayor *et al.*, 2006). After the end of experiments water loss and solid gain were calculated by the following equations (Chenlo *et al.*, 2006):

$$WL = \frac{(1-S_0)m_0 - (1-S_t)m_t}{S_0 m_0} \tag{1}$$

$$SG = \frac{S_t m_t - S_0 m_0}{S_0 m_0} \tag{2}$$

Where, m_0 is the initial mass of the sample, m_t is the sample mass at time t, S_0 and S_t are the solids content of the sample prior to osmotic dehydration and the solids content of the sample after osmotic dehydration at time t, respectively.

It should be noted that, in order to measure moisture content, rehydrated samples were withdrawn from osmotic solutions and after removal of excess surface water using filter paper, placed in a petri dish and moved to a hot air convective oven (model UNE 400 PA; Memmert) and dried at 105 °C for 48 h, then the moisture content was calculated by following equation:

$$MC(d.\mathrm{b}\%) = \frac{W_w}{W_i - W_w} \quad (3)$$

Where, W_w is the mass of evaporated water and W_i is the initial mass of the sample after rehydration.

Artificial neural network

In order to obtain the best prediction of courgette osmotic dehydration parameters by neural network, multilayer perceptron network (MLP) was used with different architectures and trained using the experimental data (Aghajani *et al.*, 2012; Kashiri *et al.*, 2012; Mokhtarian *et al.*, 2014a,b). The network arrangement architecture was based on 4 inputs and 2 outputs (Figure 1). The input layer consists of osmotic solution concentration (x_1) osmotic solution temperature (x_2), immersion time (x_3) and pre-treatment type (x_4) and the output layer contains water loss (y_1) and solid gain (y_2). The back propagation algorithm was used in the training of ANN model. This algorithm uses the supervised training technique where the network weights and biases are initialised randomly at the beginning of the training phase (Tavakolipour and Mokhtarian, 2012). In this work, Number of 1-2 hidden layers with 2-50 neurons per hidden layer, learning rate = 0.4, momentum coefficient = 0.9 and activation functions of sigmoid logarithms (Equation 4) and hyperbolic tangent (Equation 5) in both hidden and output layers were used in order to find the best configuration.

$$\log sig(z) = (1+\exp(-z))^{-1} \qquad (0,+1) \quad (4)$$

$$\tanh(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}} \qquad (-1,+1) \quad (5)$$

Computer program SPSS version 17 (2011; IBM Corp., Armonk, NY, USA) was used to design and evaluation of ANN performance by determination of two important criteria such as correlation coefficient (R^2) and mean relative error (MRE) according to the following equations:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N} (U_{p,i} - U_{e,i})^2}{\sum_{i=1}^{N} (\bar{U}_{p,i} - U_{p,i})^2} \right] \quad (6)$$

$$MRE = \left(\frac{1}{N} \sum_{i=1}^{N} \frac{\left| U_{p,i} - U_{e,i} \right|}{U_{e,i}} \right) \times 100 \quad (7)$$

Where $U_{p,i}$ is predicted data, $U_{e,i}$ is experimental data, $\bar{U}_{p,i}$ is average of experimental data and *N* is the number of observations.

Statistical analysis method

Results were analysed by statistics software (version 8; Analytical Software, Tallahassee, FL, USA) and analysis of variance (ANOVA) method. Means comparison was made by LSD tests at the probability of 0.01%.

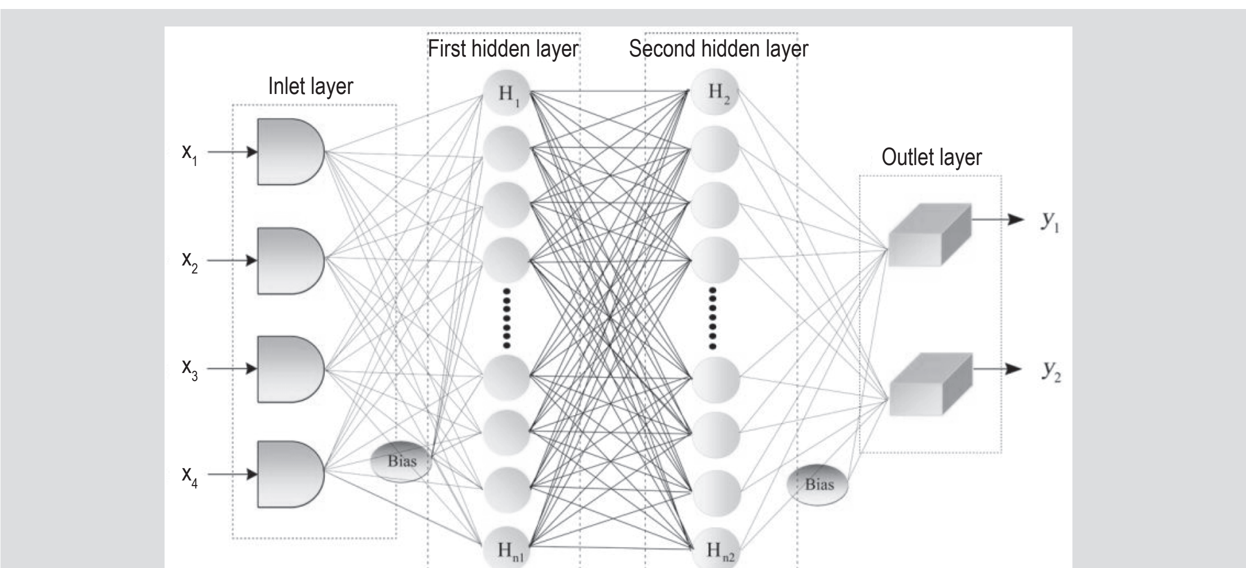

Figure 1. Schematic structure of multi-layer perceptron neural network (x_1 = osmotic solution concentration; x_2 = osmotic solution temperature; x_3 = immersion time; x_4 = treatment type; y_1 = water loss; y_2 = solid gain).

3. Results and discussion

Water loss

The effect of treatment type and osmotic solution concentration on the amount of water loss is shown in Figure 2A. The experimental results indicated that the osmotic solution concentration and the type of treatment had a meaningful effect on water loss (P<0.01). As can be seen from Figure 2A, by increasing the solution concentration from (sucrose 35% + sorbitol 5%, w/v) to (sucrose 35% + sorbitol 15%, w/v), the rate of water loss, increased during 120 min of osmotic dehydration process, this was in agreement with other research (Khin *et al.*, 2007). The maximum water loss was obtained when the osmotic treatment was carried out in the highest concentrated solution (i.e. sucrose 35% + sorbitol 15%, w/v). As can be seen from Figure 2A, the maximum water loss in courgette was related to ultrasound assisted osmo-dehydrated samples. Similar results were reported by García-Noguera and his co-workers regarding that used ultrasound treatment in osmotic dehydration of strawberry in sucrose osmotic solution (García-Noguera *et al.*, 2010). Increasing the osmotic solution concentration decreased water activity and increased the necessary derived force for water removal from sample tissue, which lead to an increase in the water loss (Eren and Kaymak-Ertekin, 2007). Additionally, by increasing osmotic solution concentration, the osmotic pressure difference was maintained for a longer time and better mass transfer and higher water losses were achieved (Togrul and Ispir, 2007).

The effect of osmotic solution temperature and the kind of treatment on water loss was shown in Figure 2B. As can be seen, by rising osmotic solution temperature, the amount of water loss of courgette slice increased, so that the dehydrated sample at 50 °C had the highest amount of water loss and dehydrated sample at 5 °C had the lowest amount of water loss. Ultrasound treatment had a significant effect on the amount of water loss in the osmotic dehydrated sample. Increase osmotic solution temperature reduces the viscosity of osmotic solution and external mass transfer resistance which reduced water transport from courgette slice during osmotic dehydration process (Lertworasirikul and Saetan, 2010). On the other hand, by rising osmotic solution temperature, increased the membrane permeability, swelling and shrinkage of cellular membrane that facilitates the rate of water loss from sample (Eren and Kaymak-Ertekin, 2007).

ANOVA results showed that (Figure 2), the kind of treatment had meaningful and significant effect (P<0.01) on water loss. The highest values of water loss were shown in treated samples with ultrasound that this due to the cavitation phenomenon caused by sonication that this effect can increase the mass transfer rate during osmotic processes and accelerates the rate of water loss (Sun, 2005).

Solid gain

Figure 3 shows the experimental data for solid gain under the experimental conditions tested in this research. The results illustrated that the most significant (P<0.01) changes of solid gain took place during the 120 min of osmotic dehydration in ultrasound treated samples. As can be seen from Figure 3A, increasing the concentration of osmotic solution from 5%, w/v to 15%, w/v sorbitol, lead to an increase in the amount of solid gain in both ultrasonicated and non-ultrasonicated courgette slice. Other researchers have shown that the amount of solid gain increased with an increase of the osmotic solution concentration and application ultrasound treatment

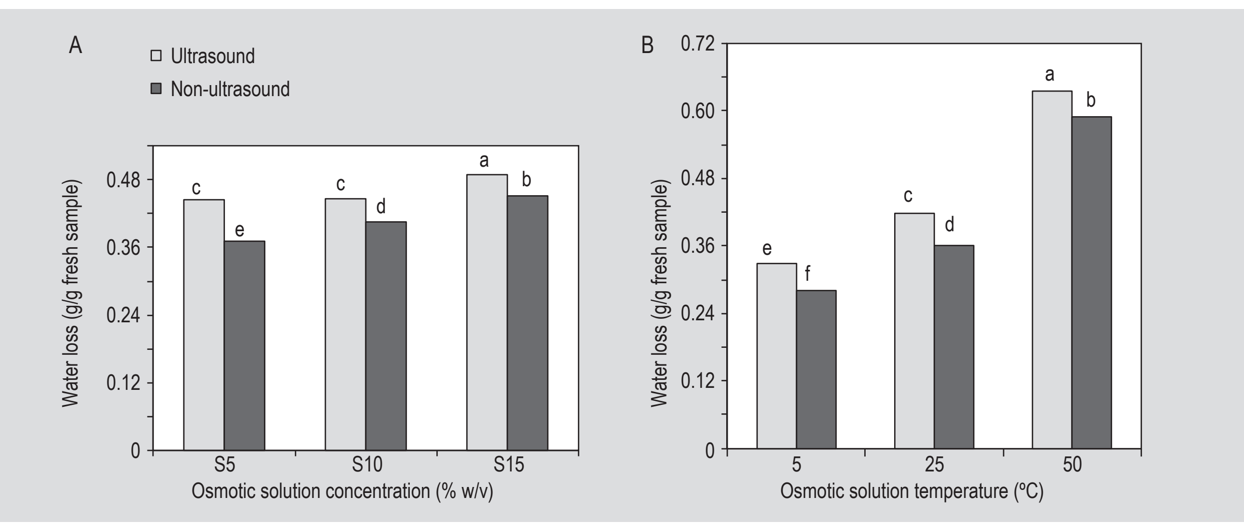

Figure 2. The effect of (A) osmotic solution concentration and (B) temperature on water loss during 120 min of ultrasound and non-ultrasound assisted osmotic dehydration process (S_5 = sucrose 35% + sorbitol 5%, w/v; S_{10} = sucrose 35% + sorbitol 10%, w/v; S_{15} = sucrose 35% + sorbitol 15%, w/v). Columns with the same superscript letter are not statistically different (*P*<0.01).

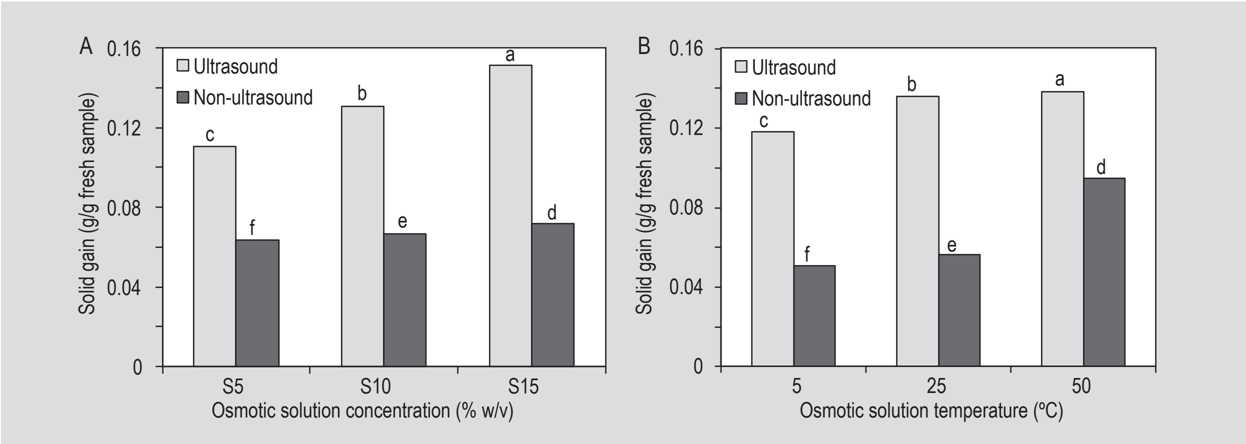

Figure 3. The effect of (A) osmotic solution concentration and (B) temperature on solid gain during 120 min of ultrasound and non-ultrasound assisted osmotic dehydration process, (S_5 = sucrose 35% + sorbitol 5%, w/v; S_{10} = sucrose 35% + sorbitol 10%, w/v; S_{15} = sucrose 35% + sorbitol 15%, w/v). Columns with the same superscript letter are not statistically different (*P*<0.01).

(Fernandes *et al.*, 2008; García-Noguera *et al.*, 2010; Singh *et al.*, 2007). The increase of solid gain may be due to increases water loss, which leads to an increase in solute concentration inside courgette rings, this is in agreement with the results of Jalaee *et al.* (2011). Furthermore, the increase in diffusion rates of solute into courgette tissue may be due to the lower molecular weight of sorbitol than sucrose. An increase of osmotic solution concentration from 5%, w/v to 15%, w/v sorbitol lead to an increase in the solid gain in courgette slices. Several researchers have stated that Osmo-active substance with lower molecular weight lead to significantly greater solid gain compared with other osmotic agents with higher molecular weight. This could be due to the lower diffusivity of higher molecular weight substances (Kowalska *et al.*, 2008; Mayor *et al.*, 2006).

As can be seen from Figure 3B, there was an increase in the amount of solid gain with an increase of osmotic solution temperature. The highest amount of solid gain was related to osmo-dehydrated courgette slices at 50 °C and the lowest amount was at 5 °C. Treated samples with ultrasound had a higher solid gain compared to non-ultrasonicated samples. These results are in accordance with those obtained by other researchers (García-Noguera *et al.*, 2010; Singh *et al.*, 2007). The impact of increasing solution temperature may be due to a decrease of the osmotic solution viscosity which leads to higher diffusion rates of solute into the courgette tissue (El-Aouar *et al.*, 2006; Fernandes *et al.*, 2008; Singh *et al.*, 2007).

Moisture content

The average initial moisture content of courgette slices was found to be 18.49±1.61% (dry basis). The final moisture content of courgette samples, as a function of osmotic solution concentration in two different treatments of ultrasound and non-ultrasound assisted osmotic dehydration during 120 min of osmotic process, are presented in Figure 4A. Statistical analysis showed that the effect of osmotic solution concentration and treatment on the final moisture content is quite significant (P<0.01). The highest final moisture content was found in non-ultrasound assisted osmotic dehydrated courgette slice with sucrose 35% + sorbitol 5% w/v osmotic solution (i.e. S_5) and the lowest final moisture content was observed in ultrasound assisted osmotic dehydrated courgette slice with sucrose 35% + sorbitol 15%, w/v osmotic solution (i.e. S_{15}). This may be due to the cavitation phenomenon caused by sonication, this effect can increase moisture diffusion during osmotic processes and accelerate dehydration of the tissue (Sun, 2005).

The effect of osmotic solution temperature on the final moisture content with respect to treatment type is shown in Figure 4B. Statistical analysis revealed that by increasing the solution temperature the final moisture content of courgette decreased. Furthermore, the result indicated that ultrasound assisted osmotic dehydration lead to a higher reduction in the final moisture content. Increasing osmotic solution temperature led to sample swelling and more water diffusion from the sample (Eren and Kaymak-Ertekin, 2007; García-Noguera *et al.*, 2010). These results are in agreement with previous researchers (Kowalska *et al.*, 2008; Mokhtarian *et al.*, 2014b).

Artificial neural network modelling of ultrasound assisted osmotic dehydration parameters

In this work, a combination of the layers and neurons with different activation functions was used for modelling perceptron neural network. The neural network includes one and two hidden layers, 2 to 50 neurons were selected randomly and network power was estimated to predicting mass transfer factors of ultrasound assisted osmotic dehydrated courgette sample. In order to identify a suitable learning epoch, one

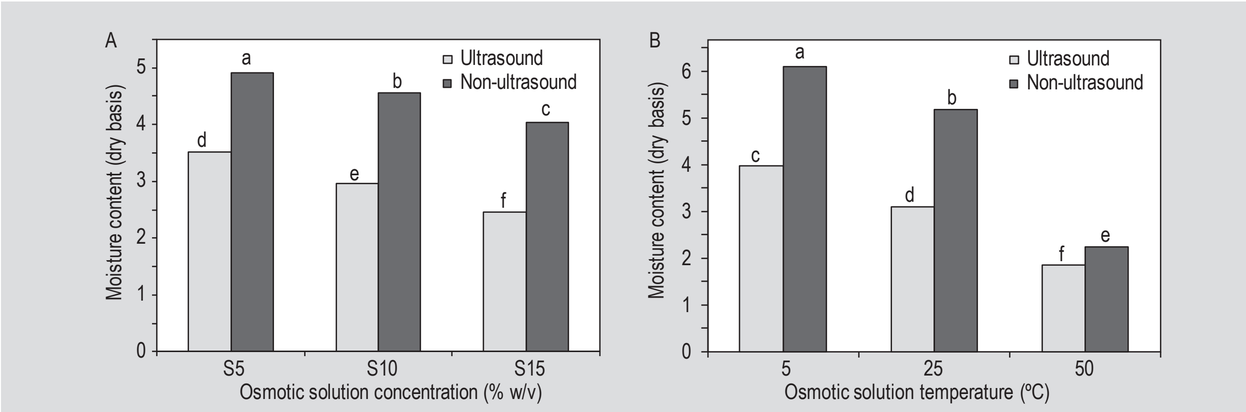

Figure 4. The effect of (A) osmotic solution concentration and (B) temperature on moisture content during 120 min of ultrasound and non-ultrasound assisted osmotic dehydration process (S_5 = sucrose 35% + sorbitol 5%, w/v; S_{10} = sucrose 35% + sorbitol 10%, w/v; S_{15} = sucrose 35% + sorbitol 15%, w/v). Columns with the same superscript letter are not statistically different (*P*<0.01).

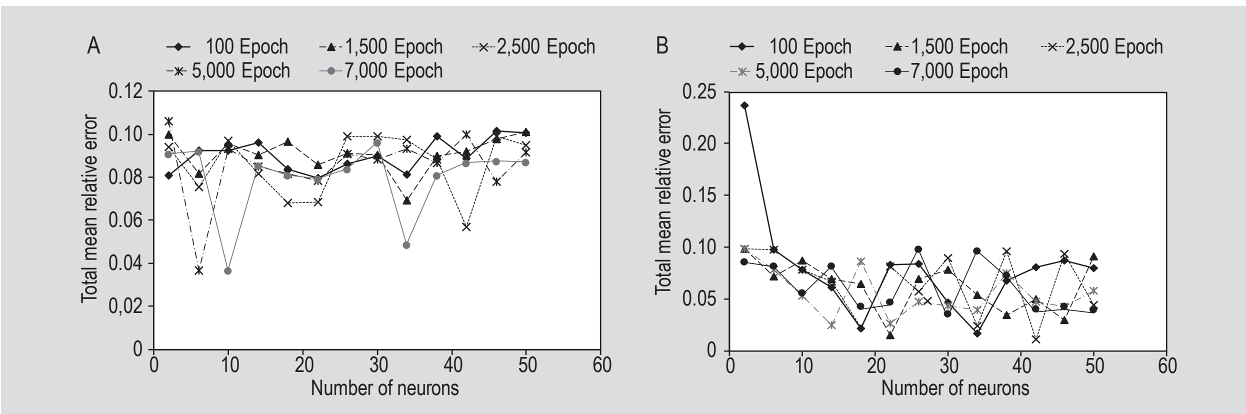

Figure 5. Determination of suitable learning epoch for different activation functions: (A) logarithm sigmoid and (B) tangent hyperbolic.

experimental network includes various neuron numbers (2 to 50 neurons), different activation functions (logsig and tanh) and different learning epochs (100, 1,500, 2,500, 5,000 and 7,000). The results showed that the best learning epochs for logarithm sigmoid and tangent hyperbolic activation functions were obtained 7,000 and 5,000, respectively. Optimisation of the best learning epoch in both activated functions lead to the lowest MRE. Determination of a suitable learning epoch for different activation functions was based on the trial and error method (Figure 5).

The obtained results of MLP network for water loss and solid gain with *logsig* and *tanh* activation functions and different configurations are shown in Figure 6. The result of MLP with logsig activation function with one and two hidden layers and shoed that topology of 4-18-18-2 (i.e. network with 4 inputs, 18 neurons in the first and second hidden layer and 2 outputs) had the best result for predictimng water loss and solid gain. As well, the result for the perceptron neural network with tanh activation function with one and two hidden layers indicated that, the neural network with a structure of 4-46-46-2 had the best result for predicting water loss and solid gain. This network was able to predict water loss and solid gain with relative error values of 0.0071 and 0.0101, respectively. R^2 values for water loss and solid gain were obtained 0.985 and 0.938, respectively.

A comparison of the results of the different activation functions of ANN for determining the best activation function for predicting ultrasound assisted osmotic dehydration factors of courgette slice is shown in Table 1. As can be seen, all the activation functions have a higher ability to predict ultrasound assisted osmotic dehydration parameters and R^2 values in all cases were higher than 0.831. However, the tanh activation function with 5,000 learning epoch lead to the best results for predicting water loss and solid gain with R^2 of 0.985 and 0.938, respectively. Generally, in the case of ultrasound assisted osmotic dehydrated courgette slices, the tanh activation function was selected as the best function due to the lower relative error and is recommended for industrial applications.

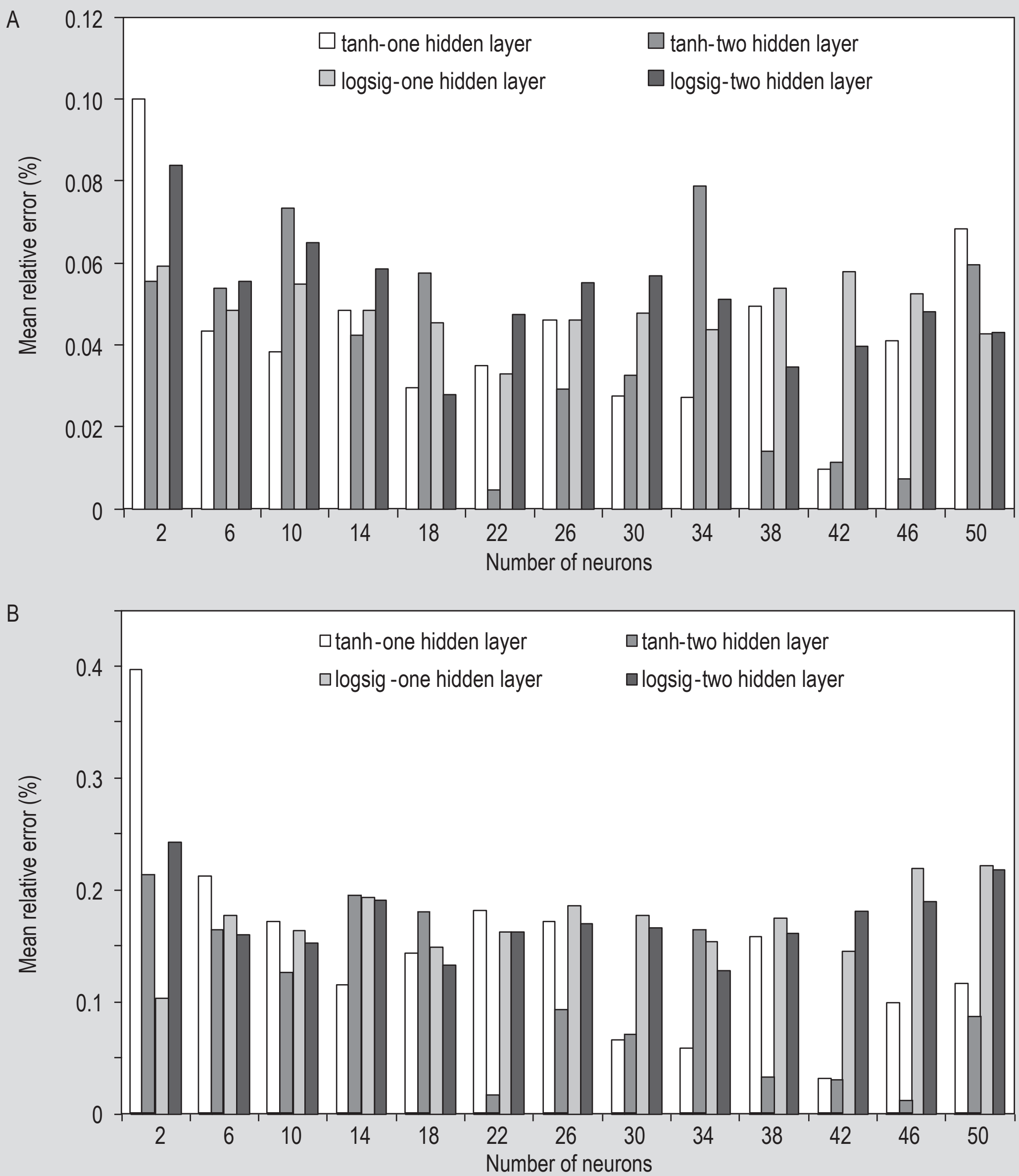

Figure 6. The variation of relative error values versus neuron number to predict (A) water loss and (B) solid gain with different activation function (tanh = tangent hyperbolic; logsig = logarithm sigmoid).

Table 1. Comparison of the different activation functions of the multilayer perceptron network to predict ultrasound assisted osmotic dehydration parameters of courgette.

Activation function	Learning epoch	Statistical parameters	Water loss	Solid gain
Logarithm sigmoid	7,000	Correlation coefficient	0.965	0.865
		Mean relative error	0.0278	0.1333
		Configuration[1]	4-18-18-2	4-18-18-2
Tangent hyperbolic	5,000	Correlation coefficient	0.985	0.938
		Mean relative error	0.0071	0.0101
		Configuration	4-46-46-2	4-46-46-2

[1] 4-N_1-N_2-2: N_1 and N_2 were the number of neurons in the first and second hidden layer, respectively.

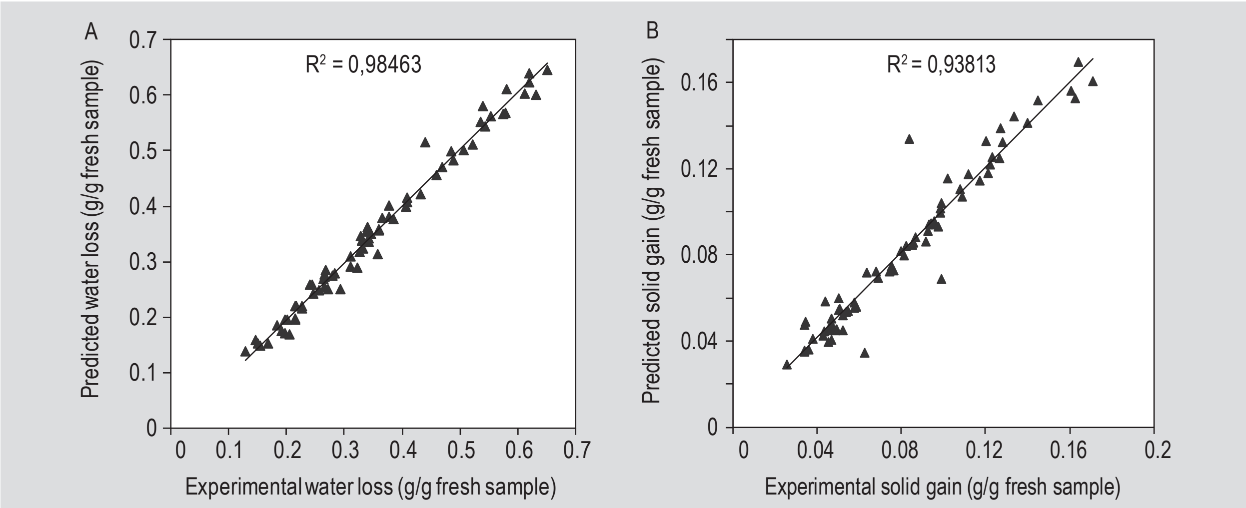

Figure 7. Predicted and experimental values of the multilayer perceptron network with tanh activation function to predict mass transfer parameters of courgette in ultrasound assisted osmotic dehydration.

Figure 7 shows the model sensitivity diagram of predicted values of multilayer perceptron network with tanh activation function vs experimental values for the best configuration (i.e. structure of 4-46-46-2). The result indicate that, the data were randomly located around the regression line. This could be a reason for carefully evaluation of the neural networks to predict ultrasound assisted osmotic dehydration parameters of courgette sample (Figure 7).

4. Conclusions

In this research the effects of ultrasound and osmotic dehydration treatments on the water loss and solid gain were studied. The results indicated that, the use of ultrasound-assisted osmotic dehydration, increased water loss and sugar gain during the process. Also, osmotic dehydration rate increased with an increase in the concentration in the osmosis solution and with process temperature. In this study an ANN trained by back propagation algorithms was developed to predict water loss and solid gain. The tanh activation function was selected as the best function due to a lower relative error and is recommended for industrial applications. This activation function was able to predict water loss and solid gain with correlation coefficients of 0.985 and 0.938, respectively.

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