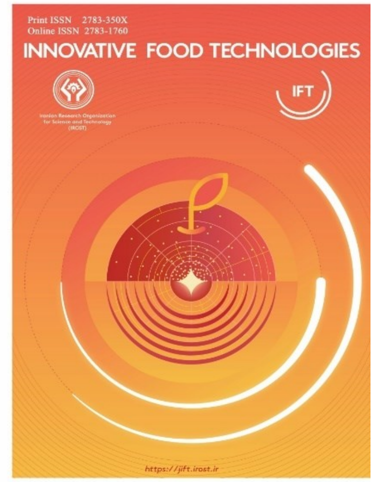
Journal Pre-proofs



Prediction of Mass Transfer during Osmotic Dehydration of Black Fig Fruits (*Ficus carica*) in Ternary Systems: Comparison of Response Surface Methodology and Artificial Neural Network

Neda Maftoonazad [1*], Akbar jokar[2] and Mashallah Zare[3]

DOI: https://doi.org/10.22104/IFT.2023.6155.2136

To appear in: Innovative Food Technologies (IFT)

Received Date: 3 March 2022

Revised Date: 28 April 2023

Accepted Date: 5 June 2023

Please cite this article as: Neda Maftoonazad [1*], Akbar jokar[2] and Mashallah Zare[3] , Prediction of Mass Transfer during Osmotic Dehydration of Black Fig Fruits (*Ficus carica*) in Ternary Systems: Comparison of Response Surface Methodology and Artificial Neural Network, *Innovative Food Technologies* *(2023)*, doi: https://doi.org/10.22104/IFT.2023.6155.2136

Prediction of Mass Transfer during Osmotic Dehydration of Black Fig Fruits (*Ficus carica*) in Ternary Systems: Comparison of Response Surface Methodology and Artificial Neural Network

Neda Maftoonazad [1*], Akbar jokar[2] and Mashallah Zare[3]

[1]Research Associate Professor, [2]Assistant Professor and [3]Food Science Technician

Agricultural Engineering Research Department, Fars Agricultural and Natural Resources Research and Education Center, Agricultural Research, Education and Extension Organization (AREEO), Shiraz, Fars Province, Iran

*Corresponding author: Tel: +989179122757; Fax: +987137206376

E-mail address: n.maftoon@areeo.ac.ir

Abstract

Osmotic dehydration of fig fruits (cv. Sabz) in ternary solution of water, sucrose and sodium chloride at different solution concentrations, temperature and process durations were analyzed. A comparative approach was made between artificial neural network (ANN) and response surface methodology (RSM) to predict the mass transfer parameters. Results showed that all independent variables positively decreased the weight meaning that increasing each factor resulted in increasing weight loss and this relationship was linear. Osmo-dehydrated figs had better quality compared to samples without osmosis. All four independent variables explained 94% of the weight loss, 90% moisture content reduction and 89% of the solid gain. The determined optimum processing conditions were temperature of 60°C, sucrose concentration of 70%, sodium chloride concentration of 5% and immersion time of 5h. The results showed that properly trained ANN model is found to be more accurate in prediction as compared to RSM model.

Keywords: Fig (*Ficus carica*), Osmotic dehydration, Artificial neural networks, Response surface methodology, Moisture loss, Solute gain

Nomenclature

x_1	Temperature (°C)	X_{cp}	Real value of an independent variable at the center point
x_2	Sucrose concentration (%)	n	Variation in a unit for the dimensionless value of variable k
x_3	Sodium chloride concentration (%)	x_k and x_j	Variables in equation
x_4	Contact time (h)	β_0	Model intercept coefficient
y_1	Moisture loss (%)	β_j	Interaction coefficients of linear terms
y_2	Weight reduction (%)	β_{jj}	Interaction coefficients of quadratic terms
y_3	Solid gain (%)	B_{kj}	Interaction coefficients of second order terms
WR	Weight reduction (%)	e_k	Error
ML	Moisture loss (%)	RMSE	Root mean square error
SG	Solid gain (%)	MAE	Mean absolute error
x_i	Initial fruit moisture on wet basis (g_{water}/g)	MAPE	Mean absolute percentage error
x_f	Final fruit moisture on wet basis (g_{water}/g)	MSE	Mean square error
w_i	Initial fruit mass (g)	X^2	Chi square statistics
w_f	Final fruit mass (g)	$Y_{i,e}$	Experimental value of the ith experiment
C	Mass concentration (g/m^3)	$Y_{i,p}$	Predicted value of the ith experiment by model
x_k	Dimensionless value of an independent variable	Y_e	Average value of experimentally determined values
X_k	Real value of an independent variable	n (in error prediction)	Number of experiments

1. Introduction

Fig is one of the earliest cultivated fruits that some of its varieties are dried and stored for later consumption. Fig is a very rich source of carbohydrates, fiber, minerals, vitamin, amino acids and antioxidants; so it is highly important in the diet [1].

With the production of 98,990 tons of figs and the cultivated area of 56,292 hectares in 2019, Iran is known as the fifth producer of figs in the world [2]. In 2020, the commercial value of Iran's fig product was 33.4 million dollars (fresh and dried figs) [3]; Therefore, figs have great economic value for Iran's agriculture. On the other hand the deterioration of fresh figs due to its perishability and the lack of proper storage conditions as well as inappropriate packaging and transportation conditions causes a lot of damage to this product [1]. Therefore, choosing a proper method for processing of fresh products, such as drying, can be a suitable solution to reduce fig loss and waste.

Conventional air drying; probably the oldest method used to extend the shelf life of fruits, is a simultaneous heat and mass transfer process; however, this method requires high temperatures and time, resulting in a significant degradation of important nutrient compounds and alterations in the color of the final product [4].

A pretreatment, such as osmotic dehydration, may present in the early stages of dehydration a higher rate of water loss than the rate provided by air-drying processes and can be used to reduce the initial water content, reducing total processing and air-drying time [5-7]. The osmotic process has received considerable attention as a pre-treatment since it reduces energy consumption and can improve food quality [8]. Moreover; this process helps inhibition of enzymatic browning, better retention of color and flavor with reduced water activity [9]. This dehydration process can be done in binary (water/sugar) [10] or ternary (water, sugar and salt) systems [5]. Different aspects of osmotic dehydration of food products have been investigated in the literature among which studies performed on ultrasound assisted osmotic dehydration of kiwi fruit [9], persimmon fruit [11], plum [4, 12], garlic slices [13], Cucumber slices [14], tomato [15], bioactive compounds, antioxidant capacity, color and texture of fruits and vegetables [16] and generating functional foods [17, 18] are worth mentioning.

Several factors can affect the osmotic dehydration process. Most importantly, concentration and temperature of the osmotic solution, type of solute used to prepare the osmotic solution, shape and size of the material, mass and surface, the ratio of product to solution, contact time between product and osmotic solution, and agitation speed [7, 19-22].

Some authors have developed models to predict mass transfer kinetics of an OD process [20, 23-27]. Response Surface Methodology (RSM) is a widely and effectively used method in process and product improvement. RSM is a collection of statistical techniques for designing experiments, building models, evaluating the effects of factors and searching for optimum conditions. It is widely also employed for multivariable optimization studies. Studies on the optimized conditions for the osmotic dehydration process using RSM have been published for papaya, yam bean, potato, diced pepper, and banana [22, 26, 28-30]. Non-linear models have been suggested in food processing due to the nonlinear behavior of food products. Artificial Neural Network (ANN) models are widely used for prediction of mass transfer in the osmotic dehydration phenomenon [7, 31-33]. ANN is a powerful modeling technique that offers several advantages over conventional modeling techniques because it can model based on no assumptions concerning the nature of the phenomenological mechanisms and understanding the mathematical background of problem underlying the process as well as the ability to learn linear and nonlinear relationships between variables directly from a set of examples [31, 34]. ANN models can be classified into two classes: supervised networks and unsupervised networks. Supervised networks require a training algorithm and a training data set to adjust the connection weights, while unsupervised networks can adjust weights by themselves to achieve the required results without using any training algorithm. Supervised networks are mostly used for classification, prediction, and function approximation, while unsupervised networks are used for clustering and content addressable memory. For prediction and control of food processing operations, supervised networks are suitable [32].

No study on osmotic dehydration of Fig fruits using ternary system is still found in the literature. The objective of this work was to determine the effect of temperature, sucrose and sodium chloride concentration and immersion time on moisture loss (WL), solid gain (SG) and weight reduction (WR) during osmotic drying of fig fruits. A number of experiments were carried on based on central composite rotational design (CCRD) to collect the output variables. The performance of ANN was then compared with the performance of RSM models.

2. Materials and Methods

Black Fig fruits were provided by Fig Research Station (Estahban, Fars Province, Iran). Moisture content was determined by oven drying at 105ºC for 24 h. The osmotic solution used in each experiment was prepared by mixing food grade sucrose and sodium chloride with distilled water. The concentrations of sugar and salt, temperature of the solution and the time of immersion for each experimental run were designed based on a CCRD with four independent variables and 31 runs. The osmotic solution to fruit ratio was 4:1 to avoid an excessive dilution of the osmotic solution, maintain the osmotic solution to fruit ratio constant and maintain a good mixing in the osmotic dehydration apparatus [5]. Over-dilution of osmotic solution can reduce the mass transfer coefficient and increase the processing time throughout the experiment. Each experimental group included five random individually weighed samples. The experiment was carried out in a water bath equipped with a mechanical stirrer to maintain uniform temperature and concentration throughout the experiment. To avoid fruit decomposition and cooking, the temperature used was in the range of 30-70 °C. After removal from the solution, the dehydrated samples from each group were drained and blotted with absorbent paper to remove the excess solution. Weight and moisture content of the samples were measured individually and used to calculate the response variables of the experimental planning, including moisture loss (ML), solid gain (SG), and weight reduction (WR) according to Eqs. 1, 2 & 3, respectively [35]:

$$ML(\%) = \frac{w_i X_i - w_f X_f}{w_i} \times 100 \qquad (1)$$

$$SG\,(\%) = \frac{[w_f.(1-X_f) - w_i.(1-X_i)]}{w_i} \times 100 \qquad (2)$$

$$WR(\%) = \frac{w_i - w_f}{w_i} \times 100 \qquad (3)$$

After removal from the osmotic solution, the dehydrated sample was discharged and transferred to a circulating air dryer. The drying temperature was 60ºC and the speed of air was 1.5 m/s.

2.1. Experimental design

RSM is an empirical statistical modeling technique that is employed for multiple regression analysis using quantitative data obtained from properly designed experiments to solve multivariate equations simultaneously [31]. A CCRD with four factors at five levels was used to evaluate each main effect as well as the interaction effects. The four independent variables were temperature (x_1), sucrose concentration (x_2), salt concentration (x_3), and time of immersion (x_4). The CCRD included 31 experiments with 7 central points. Each independent variable was coded at five levels (-2, -1, 0, 1 and 2). Coding of the variables was done according to Eq. 4:

$$x_k = \frac{X_k - X_{cp}}{\Delta X_k} \quad i = 1, 2, 3, \ldots\ldots n \tag{4}$$

The obtained data were analyzed to fit a polynomial equation to each dependent variable (*ML, WR and SG).* A quadratic model, which also includes the linear model, can be described follows:

$$y = \beta_0 + \sum_{k=1}^{n} \beta_j x_k + \sum_{j=1}^{n} \beta_{jj} x_k^2 + \sum_i \sum_{,j=2}^{n} \beta_{kj} x_k x_j + e_k \tag{5}$$

The experimental data were analyzed using multiple regressions, and the significance of regression coefficients was evaluated by *F*-test. Modeling was started with a quadratic model, including linear, squared, and interaction terms, and the model adequacies were checked in terms of the values of R^2, adjusted R^2, and prediction error sum of squares. SAS software (1999) was used to perform stepwise procedure to find significant terms and simplify the models. The analysis of variance (ANOVA) and regression coefficient calculation were carried out using Microsoft Excel. The regression coefficients were used to generate response surface plots from the regression models. MATLAB software (ver. 8.5.0, R2015a) was used to build ANN models.

2.2. Optimization

The osmotic process condition was optimized using the desirability function (Myers et al. 2016). The general approach to analyzing the desirability function involves the transformation of each estimated response, variable Yi, to a desirability value, di, where $0 \leq di \leq 1$. The transformed response, di, can have many different shapes. A zero response represents a completely undesirable response, whereas a response of one represents the most desirable response. The overall desirability combines the di, of several responses using the geometric mean for simultaneous optimization of the responses (Eq. (6)):

$$D = (d_1 * d_2 * d_3 * \ldots\ldots .* d_n)^{\frac{1}{n}} \tag{6}$$

where *di* indicates the desirability of the response and *n* is the number of responses in the measure [36]. In the present study, a desirability function was developed to maximize ML and WR and minimize SG. Optimization was performed using Design Expert program version 12.0 (Statease Inc., Minneapolis, USA, trial version).

2.3. Sensory evaluation

Trained sensory panelists rated the main sensory properties of the osmotic dehydrated figs (representative samples corresponding to OD optimized conditions, as estimated by RSM) as well as control dehydrated samples (without osmotic pretreatment). Scores were given for each parameter separately on a 1–9 intensity scale (1, the lowest intensity–9, the highest intensity): red-purple color, shine, shrinkage, hardness, adhesiveness, chewiness, sweetness and saltiness and overall acceptability [15].

2.4. Artificial neural network (ANN) modeling

AANs can be used as an alternative to polynomial regression-based modeling tools that allow modeling of complex nonlinear relationships. A widely used ANN model for predicting and controlling food processing operations is a multi-layer feed forward neural network (Fig. 1). This network can learn nonlinear and complex relationships using a training algorithm with a set of input-output pairs [32]. A model was developed to predict the percentages of ML (y_1), SG (y_2) and WR (y_3) of osmodehydrated fig fruits based on four input variables; process temperature (x_1), sucrose concentration (x_2), sodium chloride concentration (x_3), and immersion time (x_4):

Data were randomized and divided into three subsets for cross validation. The first subset was the training set (70%), which was used for computing the gradient and updating the network weights and biases. The second subset was the cross validation set (15%), which was used to prevent over-fitting. The last subset was the test set (15%), which was not used during the training but to examine the network's generalization capability [37]. Due to the different ranges of each input and each output, the inputs and outputs were normalized into the interval [-1, 1] before feeding into the network. The training process was run by trial- and- error search method until a minimum of root mean square error (RMSE) was reached in the validation process. The performance of the trained network was estimated based on the accuracy of the neural network to produce outputs that are equal or near to the target (predicted) values.

The model was designed using the ANN toolbox in MATLAB (ver. 8.5.0, R2015a) and Levenberg-Marquardt (Trainlm) algorithm. Trainlm is a network training function that updates weight and bias states according to Levenberg-Marquardt optimization. A logarithmic sigmoid transfer function (logsig) was used in the first layer of the network (Eq. 7), and a linear transfer function (purelin) was used in the second layer (Eq. 8):

$$logsig(x) = \frac{1}{1+exp^{-x}} \quad (7)$$

$$purelin(x) = x \quad (8)$$

There are no strict rules for deciding which hidden layers and nodes are needed. To our knowledge, one hidden layer is sufficient though, there are subtle benefits to using two hidden layers. Therefore, we set the number of hidden layers to 1 while checking the number of neurons in the hidden layer. For this purpose, the number of 1, 5, 10, 15 and 20 neurons were used for neural network modeling and the ability of the network in predicting osmotic parameters was estimated.

2.4. Models evaluation parameters

In order to evaluate the goodness of fitting and prediction accuracy of the constructed models, error analyses (root mean square error (RMSE), mean absolute percentage error (MAPE), and and correlation coefficients (R^2) were carried out on the experimental and predicted data (Eqs. 9-11). The formulas used for the error analyses are listed in Table 1.

Table 1- Error functions and the corresponding equations

جدول (۱)-توابع خطا و معادلات مربوطه

3. Results and Discussion

3.1. RSM modeling

According to the outcome of CCRD, we found the optimal combination and conducted experiments to investigate the effect of process parameters on ML, WR and SG of osmotic dehydrated samples. Linear, interactive and quadratic models were fitted to the experimental data to obtain the regression models. Sequential model sum of squares and model summary statistics were carried out to check the adequacy of the models. Multiple regression analysis of the experimental data yielded second-order polynomial models for predicting ML, WR, and SG. A polynomial regression was used to test the effect of several factors (each time the effect of two independent variables on one dependent variable was investigated) and based on the results, the following models were obtained for each dependent variable (Eqs. 12- 14):

$$WR = 13.6 + 4.07\,X_1 + 1.75\,X_2 + 1.30\,X_3 + 2.18\,X_4 + 2.06\,X_2 * X_4 \quad (12)$$

$$WL = 9.81 + 4.16\,X_1 + 2.17\,X_2 + 1.44\,X_3 + 1.72\,X_4 \quad (13)$$

$$SG = 11.16 - 1.55\,X_2 + 1.45\,X_3 - 2.37\,X_1^2 - 3.33\,X_2^2 - 1.67\,X_4^2 + 1.76\,X_1 * X_2 \quad (14)$$

The adequacy and fitness of the models were tested by analysis of variance (ANOVA). The results indicated that the equation adequately represented the actual relationship between the independent variables and the responses (Table 2). The ANOVA results for ML, WR and SG showed relatively large *F*-value, implying that the model is significant and the values of $Adj\ R^2$ greater than 0.600 confirm the model's adequacy and fitness. The value of standard deviation is also low, indicating that the deviations between the experimental and predicted values are low.

Table 2- ANOVA for the experimental results of CCRD

جدول (۲)- آنالیز واریانس داده‌های حاصل از طرح مرکب مرکزی چرخش پذیر

Figures 1-3 display the results of osmotic dehydration. WR was greatly affected by sodium chloride and sucrose concentrations, temperature, and soaking time. The effect of temperature on dehydration was greater than that of other parameters. All four independent variables had a positive effect on WR. In other words, increasing any of the mentioned variables improved WR. The effect of all independent variables on WR was linear. At the highest concentration of sucrose (70% w/w) and the lowest amount of sodium chloride (0% w/w), the WR was almost 11%, while with the addition of 10% w/w of salt, the amount of WR increased to 17% (Fig. 1a). Fig. 1b shows that the largest value of WR could be obtained by the highest amount of sucrose content after 5 h. The effect of sodium chloride addition on enhancing the mass transfer of water was significant even at low concentrations (Fig. 1a, 1b, 1c).

Fig. 1: Response surfaces for the WR of fig fruits

شکل (۱)- منحنی‌های سطح پاسخ برای کاهش وزن میوه‌های انجیر

The regression coefficients indicated that ML is affected by the linear effects of all four independent variables as well as the interactions of sucrose content and time of immersion. In other words, ML is favored by increasing the concentrations of sodium chloride and sucrose and increasing solution temperature and immersion time (Fig. 2). ML varies from 3.35 to 31.3 g/g. The lowest ML is related to lower temperatures and lower sodium chloride contents. When temperature increases, the permeability of the cell membrane changes, leading to a better exchange of water, sucrose and sodium chloride in fruits [30]. The response surface of 2a shows that the largest values for ML are at the highest concentrations of sucrose (70% w/w) and sodium chloride (10% w/w). The response surface of ML to the concentration changes of temperature and sucrose showed that increasing the sugar content may affect ML in a wide range of temperature values (Fig. 2b). The maximum immersion time (5 h) and the maximum concentration of sodium chloride lead to the largest ML (Fig. 2c).

Fig. 2: Response surfaces for ML of fig fruits

شکل (۲)- منحنی‌های سطح پاسخ برای افت رطوبت میوه‌های انجیر

Fig. 3 indicates that SG increases with increasing the sodium chloride concentration and its effect on SG is more significant than the effect of sucrose. This means that due to the smaller molecules size, more sodium chloride than sucrose enters the fruit [5]. In this section of the study, the fig fruits samples were tested and an osmotic solution with 5% (w/w) of sodium chloride was considered to be the maximum amount of sodium chloride that can be added to the osmotic solution without changing the fruit's natural taste. This result is in agreement with the findings of Rodrigues and Fernandes (2007). The maximum SG was found at 50% (w/w) sucrose and 10% (w/w) salt concentrations (Fig.

3a). The response surface of SG to changes in temperature and sucrose content showed that the greatest value for SG was found at 50ºC and 50% (w/w) sugar. The response surface of SG to changes in temperature and time of immersion revealed that higher SG was at 50ºC after 3 h (Fig. 3b).

The response surface of SG to changes in sugar content and time of immersion showed that a wide range of contact time could be used to obtain maximum SG (Fig. 3c), while for response surface of SG to sodium chloride and contact time, it can be observed that higher SG is found at the 10% w/w after 3 h (Fig. 3d).

Fig. 3: Response surfaces for the SG of fig fruits

شکل (۳)- منحنی‌های سطح پاسخ برای جذب ماده جامد میوه‌های انجیر

Several factors may affect the infiltration process. This study tested the effects of sucrose and sodium chloride contents, temperature, and soaking time in this regard. Similar results have been obtained by other researchers for other fruits. These results may differ in the interaction effect of various factors, but all are consistent in terms of the effects of temperature, sucrose and sodium chloride content, immersion time, and some other parameters on ML, SG, and WR [30].

Increasing the temperature during the osmotic dehydration of tomato in ternary solutions led to higher water mass transfer coefficients [25]. During the osmotic dehydration of carrot cubes, ML increased by increasing the temperature [38]. The rapid ML with the increase of solution temperature might be attributed to the plasticizing effect of the cell membranes and also to the lower viscosity of the osmotic medium. Rapid ML is due to the large osmotic driving force between the dilute sap of the fresh fruit and the surrounding hypertonic solution [32, 39].

Composition of the osmotic solution has also a direct influence on the osmotic drying kinetics. The results showed that the more concentrated dehydration solution is produced, the highest ML will occur. ML and SG of the watermelon slabs treated with higher osmotic solution concentration were found to be higher [40], while in the present study, SG increased by increasing the sucrose content up to 50%. However, there is an exception in accelerating ML and SG when the solution viscosity at high concentrations begins to limit the mobility of the solution, thereby slowing down the rate of ML and SG [39].

The chemical nature of solutes, molecular weight and interaction effects have also been recognized to influence the concentration effects. Low molecular weight (LMW) solutes penetrate more readily than other compounds [39]. It seems that LMW osmotic agents can easily penetrate into the cells of fruits and vegetables as compared to HMW osmotic agents. When a mixture of sucrose-NaCl was used as the osmotic solution, higher ML were obtained due to an apparent synergistic effect of the solutes. In fact, the addition of NaCl to the solution resulted in an increase of the osmotic pressure gradients, and thus, higher ML values throughout the osmosis period. Sodium chloride increases the driving force of dehydration, lowers water activity and allows a higher rate of penetration into the material due to its low molecular weight [41]. The results of this study are in agreement with the findings of Ispir and Togrul (2009) [42]. The increase in immersion time leads to higher ML during osmotic dehydration [42, 43]. The importance of each of these parameters to the fig osmotic drying process was determined using the declared contribution or variability. The ANOVA explained the temperature, sucrose, sodium chloride and soaking time of 94% for WR, 90% for ML and 89% for SG, indicating that these values have been selected correctly**.** Similar results were reported by Abud-Archilla et al. (2008) [30].

3.2. Optimization

We determined the optimum conditions for the osmotic dehydration of fig to obtain maximum ML and WR and minimum SG. Second order polynomial models obtained in this study were utilized for each response in order to obtain specified optimum conditions. The results obtained with this experimental design showed that the fitted models for ML, WR, and SG were suitable for describing the experimental data. For optimizing the osmotic dehydration, the following were considered: temperature (30, 40, 50 & 60°C), sucrose concentration (30, 40, 50, 60 & 70%), sodium chloride (0, 2.5 & 5%) and time of immersion (1, 2, 3, 4 & 5 h). The highest levels of temperature (70°C) and sodium chloride content corresponding to the coded values of 1 and 2 (7.5 and 10%) were removed from the constraints in optimization due to their adverse effects on the final product's quality. The main criteria for optimizing the boundary conditions were the possible ML and WR, and the minimum SG. Various responses 5, 3, and 3 were used to optimize the process conditions for the osmotic dehydration of fig fruits by numerical optimization techniques based on their relative contribution to the quality of the final product, including ML, WR, and SG. The desirability approach was used to optimize the process variables to meet the criteria. The determined optimum processing conditions were temperature of 60°C, sucrose concentration of 70% sodium chloride concentration of 5% and immersion time of 5h; according to their respective desirability preferences (Table 3). At these conditions, the WR, ML and SG were obtained as 21.81, 24.10 and 3.88% (g/100g of sample), respectively with the overall desirability value of 0.794.

Table 3. Optimization criteria for different independent variables (Temperature, sucrose concentration, sodium chloride concentration and immersion time) and responses (ML, WR and SG) for optimum conditions

جدول (۳)- معیارهای بهینه‌سازی متغیر مستقل (دما، غلظت سوکروز، غلظت کلرید سدیم و زمان غوطه‌وری) و پاسخ‌های مربوطه (ML، WR و SG) در شرایط بهینه

3.3. Sensory evaluation

A sensory evaluation was performed at the optimized conditions, where the organoleptic quality of fig samples was described in terms of red-purple color, shine, shrinkage, hardness, adhesiveness, chewiness, sweetness and saltiness and overall acceptability. The intensity scores for the attributes on the hedonic scale for all samples are presented in Figure 4. Osmo-dehydrated samples had the higher scores compared to the control one for color, shine and sweetness. The scores for shrinkage, hardness, adhesiveness and chewiness were higher in control sample. By inclusion of 5%

sodium chloride no salty taste was felt. As far as the overall acceptability scores are concerned, the osmo-dehydrated sample was rated higher. It is noteworthy that despite the addition of sucrose to the pretreated samples, 90% of the panelists were satisfied with the sweetness of the processed samples. This might be due to the balance created between included sucrose and the present organic acid compounds in black figs. Control fig samples were characterized by dark color, higher shrinkage, hardness, adhesiveness and chewiness; while samples pretreated with osmotic dehydration where judged as pleasant. As mentioned in different studies, flavor/taste and texture characteristics as well as primary raw materials and solute used are the main sensory characteristic in sensory evaluation influencing the consumer acceptability of osmo-dehydrated fruits [15, 44, 45].

Fig 4. Sensory scores for the attributes on the hedonic scale (osmo-dehydrated sample at the optimum process condition and control sample). Average scores (scale 1-9) for red-purple color (axis 1), shine (axis 2), shrinkage (axis 3), hardness (axis 4), adhesiveness (axis 5), chewiness (axis 6), sweetness (axis 7), saltiness (axis 8) and overall acceptability (axis 9)

شکل (۴)- امتیازات حسی برای ویژگی‌های کیفی در مقیاس هدونیک (نمونه آب‌گیری‌شده با پیش‌فرآیند اسمز در شرایط بهینه و نمونه کنترل). میانگین امتیازات (مقیاس ۹-۱) برای رنگ قرمز-ارغوانی (محور شماره ۱)، درخشندگی (محور شماره ۲)، چروکیدگی (محور شماره ۳)، سفتی بافت (محور شماره ۴)، چسبندگی (محور شماره ۵)، قابلیت جویدن (محور شماره ۶)، شیرینی (محور شماره ۷)، شوری (محور شماره ۸) و میزان پذیرش کلی (محور شماره ۹)

3.4. ANN modeling

The ANN model was developed using a multilayer perceptron (MLP) with a sigmoid function. The first step in ANN modeling was to optimize the NN with minimal dimensions and minimal training and test errors. We trained the network using test plans and their respective test yields. The optimal number of neurons in the hidden layer of the NN was investigated by varying the number of neurons in the hidden layer and for various combinations of other parameters such as learning rate and initialization. The criterion for assessing the performance of the model was the minimum RMSE between the experimental and the corresponding predicted values. Examining the results obtained regarding the perceptron neural network with the Logsig-Purelin transfer functions with one hidden layer showed that the arrangement of 4-10-3, i.e. a network with 4 input variable, 10 nodes in the hidden layer and 3 output variable, provided the best results in prediction of ML, WR and SG (Fig 5). This network was able to predict the values of these three parameters with the correlation coefficients (R^2) of 0.910, 0.910 and 0.883 and the root mean square errors (RMSE) equivalent to 0.522, 0.497 and 0.554. Table 4 indicates the data of perceptron neural network with different numbers of neurons.

Results of this study were similar to Aydani's et al. (2013) findings in which they reported that a network with 5 inputs, 5 nodes in the hidden layer and 4 outputs has the best results in predicting the final moisture content and solid uptake of orange slices [46]. They also showed that this network with a hidden layer and the number of 30 neurons was able to predict the water reduction and Brix difference well. In another study, Azadbakht et al. (2018) found that a network containing 6 neurons in the hidden layer could successfully predict the energy efficiency ($R^2 = 0.999$) and specific energy loss ($R^2 = 0.871$) in osmotic pretreatment of microwae-dried orange slices [47]. Mokhtarian and

Tavakolipour (2016) demonstrated that an ANN model with eight neurons in one hidden layer was able to forecast water loss and solid gain with R^2 values equal to 0.967 and 0.890 where relative error values corresponding to each of these factors were estimated at 0.0205 and 0.0872, respectively; in osmotic dehydration of Crookneck squash [48].

Fig. 5: Structure of multilayer feedforward neural network

شکل (۵) – ساختار شبکه عصبی چندلایه

3.5. Comparison of RSM and ANN models

The ANN and RSM models were compared with regard to their goodness of fitting and prediction accuracy using the criteria presented in Table 1. The results of statistical analysis and comparison between RSM and ANN models are listed in Table 4. To study the modeling abilities of RSM and ANN models, the values predicted by these models were plotted against the corresponding experimental values (Figures 6a to 6c). These figures show the predicted data by ANN model were much closer to the line of perfect prediction than those of predicted by RSM models for all three dependent variables. Therefore, a significantly higher generalization capacity was observed by the ANN models compared to RSM ones. According to Maran et al. (2013) the higher accuracy of ANN models in prediction of osmotic dehydration parameters could be due to its universal ability to estimate the nonlinearity of the process, while the RSM models are confined to the second order polynomials. On the other hand, a great number of iterative computations are performed during generation of ANN models whilst in RSM models only a single step calculation is carried out [31]. In this regard, results of the present study are in the range of those previously reported [32, 46, 49]; however, different ranges of error and coefficient of determination parameters have provided in the literature.

Almost all the studies conducted in relation to the prediction of osmotic dehydration parameters using neural network have come to the conclusion that ANN approach provides a robust tool for modeling the osmotic dehydration process and that the outputs are remarkably better than conventional mathematical models in predicting the water loss and solids gain during this process. However, such operations involve highly complex and non-linear physical mechanism. In this regard we can refer to the studies conducted on osmotic dehydration of eggplant [50], pumpkin [51] and fish [52].

Table 4-Comparison between RSM and ANN models

جدول (۴) -مقایسه بین مدل‌های RSM و ANN

Fig. 6: Experimental vs. predicted values of RSM and ANN models for a) ML (%), b) WR (%) and c) SG (%)

شکل (۶) – مقادیرآزمایشی و پیش‌بینی‌شده توسط مدل‌های RSM و ANN برای الف) ML (%)، ب) WR (%) و ج) SG (%)

4. Conclusions

This paper investigated the OD process of fig fruits. All four independent variables (temperature, sucrose concentration, sodium chloride concentration, immersion time) had significant effect on responses. The use of a ternary osmotic solution improved mass transfer compared to the binary osmotic solution. The use of salt increased ML and WR, but at high concentrations, it increased SG and made the fruit too salty. The amount of sodium chloride that can be added to the osmotic solution without changing the fruit's natural taste was found to be 5% w/w. The ANOVA results showed a significant effect (*P<0.05*) of all process parameters on ML and SG. Sucrose and sodium chloride content, temperature and immersion time of the sample explained 94% of WR, 90% of ML and 89% of SG. These high percentages confirm that the parameters required for the osmotic drying process have been selected correctly. The optimal treatment conditions found were a temperature of 60 °C, a sucrose concentration of 70%, a sodium chloride concentration of 5%, and a soaking time of 5 h. Under these conditions, ML, WR, and SG were 21.81, 24.10, and 3.88% (g / 100 g samples), respectively with a desired value of 0.794. We used the experimental data based on CCRD in the osmotic dehydration process of fig fruits to model, predict, and generalize the performance of RSM and ANN methods. The results showed that the multilayer perceptron (MLP) with sigmoidal function and 10 hidden nodes was suitable for predicting WR, ML and SG of fig fruits during the OD process. In both the learning and testing processes of ANN model, the error between the predicted and experimental values for ML, WR, and SG was relatively small, and r^2 for these parameters was high. The ANN model could more accurately predict ML, WR, and SG in range of RSM model. In other words, a well-trained ANN model is more accurate in prediction than RSM.

Acknowledgments

This study was supported by the Agricultural Engineering Research Institute (AERI), Agricultural Research, Education and Extension Organization (AREEO), Shiraz, Fars Province, Iran.

References

1. Crisosto, H., et al., *Fig (Ficus carica L.)*, in *Postharvest biology and technology of tropical and subtropical fruits*. 2011, Elsevier. p. 134-160e.

2. Agricultural statistics, *Horticultural products*. 2021, Ministry of Jihad and Agriculture, Planning and Economic Deputy, Information and Communication Technology Center [In Persian].

3. Complexity, T.O.o.E. *https://oec.world/*. 2020.

4. Romero, I.P., et al., *Optimization of the osmotic dehydration process of plums (Prunus Salicina Lindl.) in solutions enriched with inulin, using response surface methodology.* LWT, 2022. **157**: p. 113092.

5. Rodrigues, S. and F.A.N. Fernandes, *Dehydration of melons in a ternary system followed by air-drying.* Journal of Food Engineering, 2007. **80**(2): p. 678-687.

6. Dhiman, S., et al., *Osmotic dehydration of mulberry: Effect of pretreatment and processing conditions on the quality attributes.* Applied Food Research, 2022. **2**(2): p. 100172.

7. Jahedi Rad, S., et al., *Fuzzy logic, artificial neural network and mathematical model for prediction of white mulberry drying kinetics.* Heat and Mass Transfer, 2018. **54**: p. 3361-3374.

8. Yu, Y., et al., *Biochemical degradation and physical migration of polyphenolic compounds in osmotic dehydrated blueberries with pulsed electric field and thermal pretreatments.* Food chemistry, 2018. **239**: p. 1219-1225.

9. Prithani, R. and K.K. Dash, *Mass transfer modelling in ultrasound assisted osmotic dehydration of kiwi fruit.* Innovative Food Science & Emerging Technologies, 2020. **64**: p. 102407.

10. Tsamo, C.V.P., et al., *Study of material transfer during osmotic dehydration of onion slices (Allium cepa) and tomato fruits (Lycopersicon esculentum).* LWT - Food Science and Technology, 2005. **38**(5): p. 495-500.

11. Bozkir, H., et al., *Influence of ultrasound and osmotic dehydration pretreatments on drying and quality properties of persimmon fruit.* Ultrasonics sonochemistry, 2019. **54**: p. 135-141.

12. Rahaman, A., et al., *Influence of ultrasound-assisted osmotic dehydration on texture, bioactive compounds and metabolites analysis of plum.* Ultrasonics sonochemistry, 2019. **58**: p. 104643.

13. Feng, Y., et al., *Vacuum pretreatment coupled to ultrasound assisted osmotic dehydration as a novel method for garlic slices dehydration.* Ultrasonics sonochemistry, 2019. **50**: p.۳۷۲-۳۶۳ .

14. Kiani, H., et al., *A novel inverse numerical modeling method for the estimation of water and salt mass transfer coefficients during ultrasonic assisted-osmotic dehydration of cucumber cubes.* Ultrasonics Sonochemistry, 2018. **44**: p. 171-176.

15. Giannakourou, M.C., A.E. Lazou, and E.K. Dermesonlouoglou, *Optimization of osmotic dehydration of tomatoes in solutions of non-conventional sweeteners by response surface methodology and desirability approach.* Foods, 2020. **9**(10): p. 1393.

16. Landim, A.P.M., M.I.M.J. Barbosa, and J.L.B. Júnior, *Influence of osmotic dehydration on bioactive compounds, antioxidant capacity, color and texture of fruits and vegetables: a review.* Ciência Rural, 2016. **46**: p. 1714-1722.

17. Nagai, L.Y., et al., *Osmotic dehydration of mango with ascorbic acid impregnation: influence of process variables.* Journal of Food Processing and Preservation, 2015. **39**(4): p. 384-393.

18. Jiménez-Hernández, J., et al., *Osmotic dehydration of mango with impregnation of inulin and piquin-pepper oleoresin.* LWT-Food Science and Technology, 2017. **79**: p. 609-615.

19. Ferrari, C.C. and M.D. Hubinger, *Evaluation of the mechanical properties and diffusion coefficients of osmodehydrated melon cubes.* International journal of food science & technology, 2008. **43**(11): p. 2065-2074.

20. Singh, B., et al., *Optimisation of osmotic dehydration of carrot cubes in sucrose-salt solutions using response surface methodology.* European Food Research and Technology, 2007. **225**(2): p. 157-165.

21. Ahmed, I., I.M. Qazi, and S. Jamal, *Developments in osmotic dehydration technique for the preservation of fruits and vegetables.* Innovative Food Science & Emerging Technologies, 2016. **34**: p. 29-43.

22. Ozdemir, M., et al., *Optimization of osmotic dehydration of diced green peppers by response surface methodology.* LWT - Food Science and Technology, 2008. **41**(10): p. 2044-2050.

23. de Oliveira, L.F., et al., *Osmotic dehydration of yacon (Smallanthus sonchifolius): Optimization for fructan retention.* LWT - Food Science and Technology, 2016. **71**: p. 77-87.

24. da Costa Ribeiro, A.S., E. Aguiar-Oliveira, and R.R. Maldonado, *Optimization of osmotic dehydration of pear followed by conventional drying and their sensory quality.* LWT - Food Science and Technology, 2016. **72**: p. 407-41.۵

25. Tonon, R.V., A.F. Baroni, and M.D. Hubinger, *Osmotic dehydration of tomato in ternary solutions: Influence of process variables on mass transfer kinetics and an evaluation of the retention of carotenoids.* Journal of Food Engineering, 2007. **82**(4): p.۵۱۷-۵۰۹ .

26. Rahman, S., P. Sharma, and Z. Said, *Application of Response Surface Methodology Based D-Optimal Design for Modeling and Optimisation of Osmotic Dehydration of Zucchini.* Digital Chemical Engineering, 2022. **4**: p. 100039.

27. Maldonado, M. and J.G. Pacheco, *Mathematical modelling of mass transfer phenomena for sucrose and lactitol molecules during osmotic dehydration of cherries.* Heliyon, 2022. **8**(1): p. e08788.

28. El-Aouar, Â.A., et al., *Influence of the osmotic agent on the osmotic dehydration of papaya (Carica papaya L.).* Journal of Food Engineering, 2006. **75**(2): p. 267-274.

29. Mercali, G.D., et al., *Evaluation of water, sucrose and NaCl effective diffusivities during osmotic dehydration of banana (Musa sapientum, shum.).* LWT - Food Science and Technology, 2011. **44**(1): p. 82-91.

30. Abud-Archila, M., et al., *Optimization of osmotic dehydration of yam bean (Pachyrhizus erosus) using an orthogonal experimental design.* Journal of Food Engineering, 2008. **84**(3): p. 413-419.

31. Prakash Maran, J ,.et al., *Artificial neural network and response surface methodology modeling in mass transfer parameters predictions during osmotic dehydration of Carica papaya L.* Alexandria Engineering Journal, 2013. **52**(3): p. 507-516.

32. Lertworasirikul, S. and S. Saetan, *Artificial neural network modeling of mass transfer during osmotic dehydration of kaffir lime peel.* Journal of Food Engineering, 2010. **98**(2): p. 214-223.

33. Ochoa-Martinez, C. and A. Ayala-Aponte, *Prediction of mass transfer kinetics during osmotic dehydration of apples using neural networks.* LWT-Food Science and Technology, 2007. **40**(4): p. 638-645.

34. Aghbashlo, M., S. Hosseinpour, and A.S. Mujumdar, *Application of artificial neural networks (ANNs) in drying technology: a comprehensive review.* Drying technology, 2015. **33**(12): p. 1397-1462.

35. Maftoonazad, N., Badii, F., Shahamirian, M., Mirmajidi, A., Zare, H. and Jokar, L. , *Using osmotic dehydration and hot air to produce intermediate moisture fig*. 2013, Publication of Agricultural Research, Education and Extension Organization. No. 43548 [In persian].

36. Myers, R.H., D.C. Montgomery, and C.M. Anderson-Cook, *Response surface methodology: process and product optimization using designed experiments*. 2016: John Wiley & Sons.

37. Lertworasirikul ,S., *Drying kinetics of semi-finished cassava crackers: A comparative study.* LWT - Food Science and Technology, 2008. **41**(8): p. 1360-1371.

38. Singh, B., et al., *Optimisation of osmotic dehydration process of carrot cubes in mixtures of sucrose and sodium chloride solutions.* Food Chemistry, 2010. **123**(3): p. 590-600.

39. Ramaswamy, *Osmotic drying: principles, techniques and modeling*, in *In Proceeding of the 5th Asia-Pasific Drying conference*. 2007: Hong Kong. p. 49-51.

40. Falade, K.O., J.C. Igbeka, and F.A. Ayanwuyi, *Kinetics of mass transfer, and colour changes during osmotic dehydration of watermelon.* Journal of Food Engineering, 2007. **80**(3): p. 979-985.

41. Antonio, G.C., et al., *Influence of osmotic dehydration and high temperature short time processes on dried sweet potato (Ipomoea batatas Lam.).* Journal of Food Engineering, 2008. **84**(3): p. 375-382.

42. İspir, A. and İ.T. Toğrul, *Osmotic dehydration of apricot: Kinetics and the effect of process parameters.* Chemical Engineering Research and Design, :(۲)۸۷ .۲۰۰۹p. 166-180.

43. Mundada, M., B.S. Hathan, and S. Maske, *Mass transfer kinetics during osmotic dehydration of pomegranate arils.* Journal of food science, 2011. **76**(1): p. E31-E39.

44. Konopacka, D., et al., *The effect of different osmotic agents on the sensory perception of osmo-treated dried fruit.* The Journal of Horticultural Science and Biotechnology, 2009. **84**(6): p. 80-84.

45. Vilela, A., et al., *Texture quality of candied fruits as influenced by osmotic dehydration agents.* Journal of Texture Studies, 2016. **47**(3): p. 239-252.

46. Aydani, E., et al., *Optimization of orange osmotic dehydration process using response surface method and estimation of dehydration parameters by Artificial Neural Network.* Iranian Food Science and Technology Research Journal, 2013. **9**(3).

47. Azadbakht, M., et al., *Application of artificial neural network method for prediction of osmotic pretreatment based on the energy and exergy analyses in microwave drying of orange slices.* Energy, 2018. **165**: p. 836-845.

48. Mokhtarian, M. and H. Tavakolipour, *The application of neural network method for the prediction of the osmotic factors of crookneck squash.* 2016.

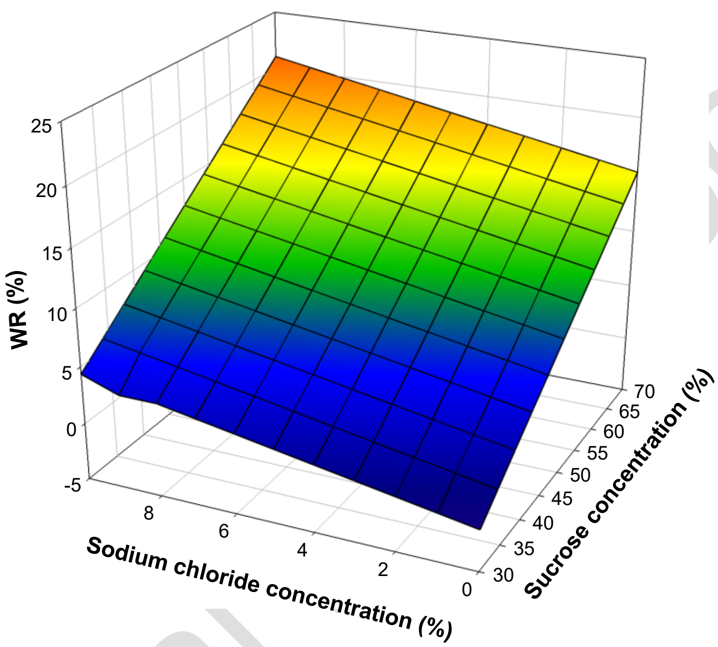
49. Morais, R.A., D.G. Alves, and W.G. Da Silva, *Use of artificial neural network to optimize osmotic dehydration process of cashew from cerrado (Anacardium occidentale).* International Journal of Computer Applications, 2016. **975**: p. 8887.

50. Bahmani, A., et al., *Mass transfer kinetics of eggplant during osmotic dehydration by neural networks.* Journal of food processing and preservation, 2016. **40**(5): p. 815-827.

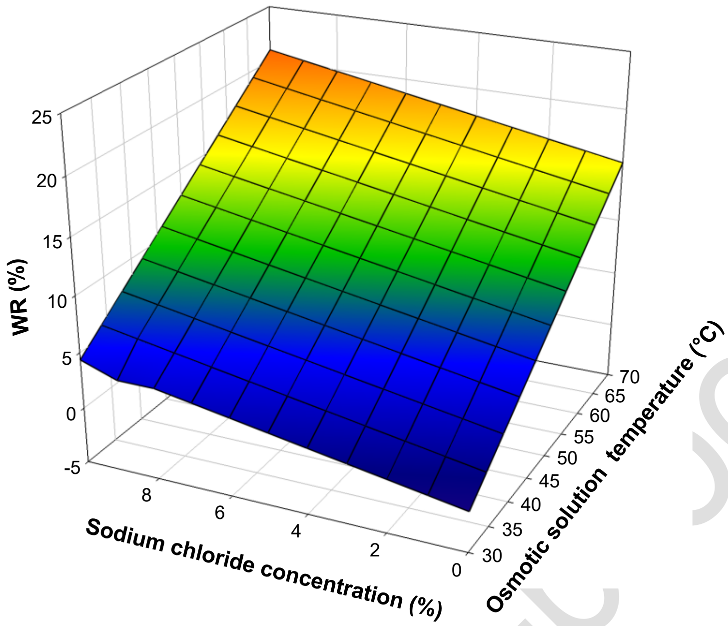
51. Mokhtarian, M., et al., *Optimisation of pumpkin mass transfer kinetic during osmotic dehydration using artificial neural network and response surface methodology modelling.* Quality Assurance and Safety of Crops & Foods, 2014. **6**(2): p. 201-214.

52. Ćurčić, B.L., et al., *Osmotic treatment of fish in two different solutions ‑ artificial neural network model.* Journal of food processing and preservation, 2015. **39**(6): p. 671-680.

a)


25
20
15
10
5
0
-5
WR (%)
8
6
4
2
0
Sodium chloride concentration (%)
30
35
40
45
50
55
60
65
70
Sucrose concentration (%)

b)



c)

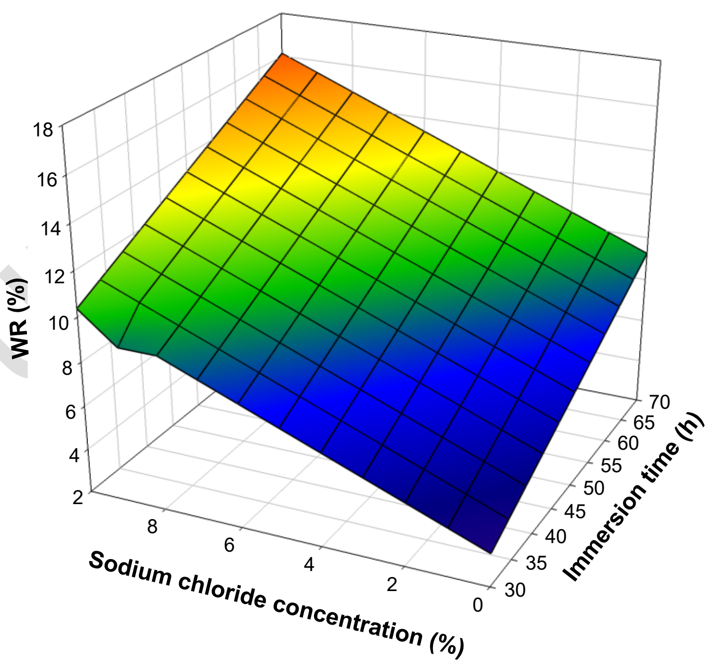
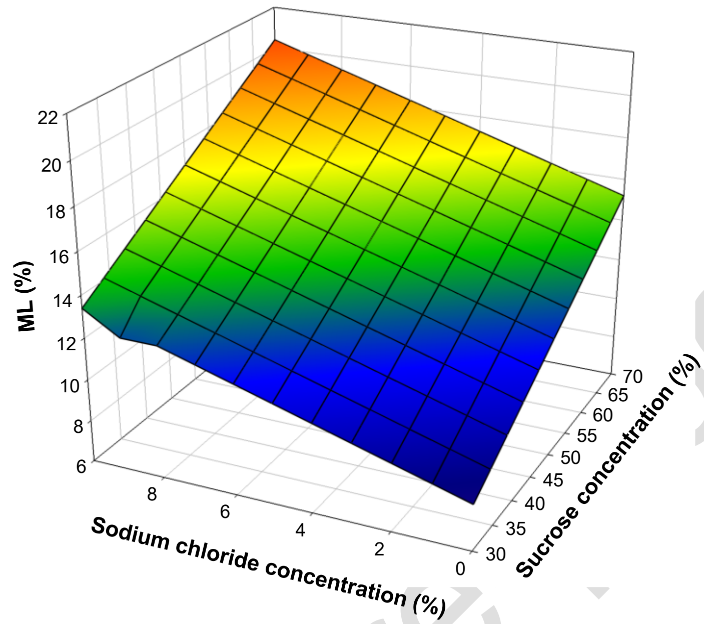
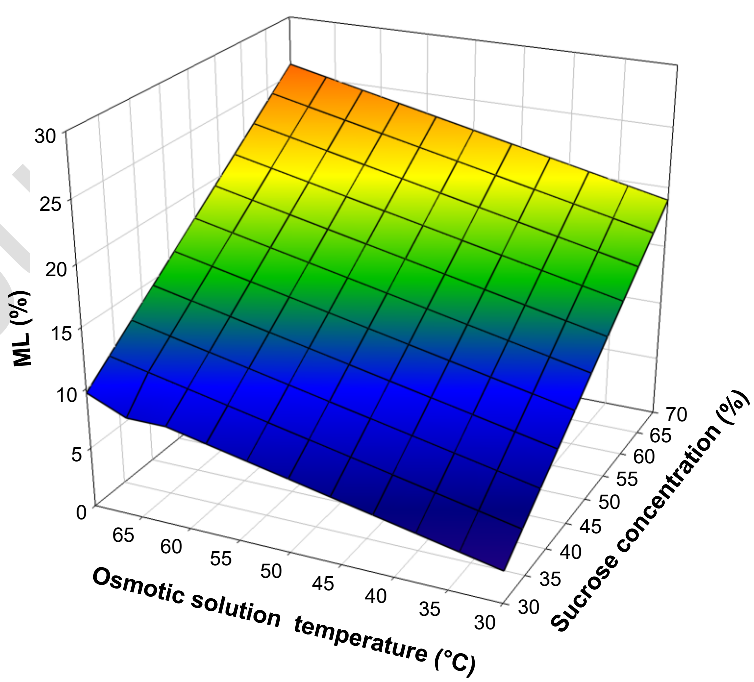


Fig. 1: Response surfaces for the WR of fig fruits

a)


22
20
18
16
14
12
10
8
6
ML (%)
8
6
4
2
0
Sodium chloride concentration (%)
30
35
40
45
50
55
60
65
70
Sucrose concentration (%)

b)


30
25
20
15
10
5
0
ML (%)
65
60
55
50
45
40
35
30
Osmotic solution temperature (°C)
30
35
40
45
50
55
60
65
70
Sucrose concentration (%)

c)

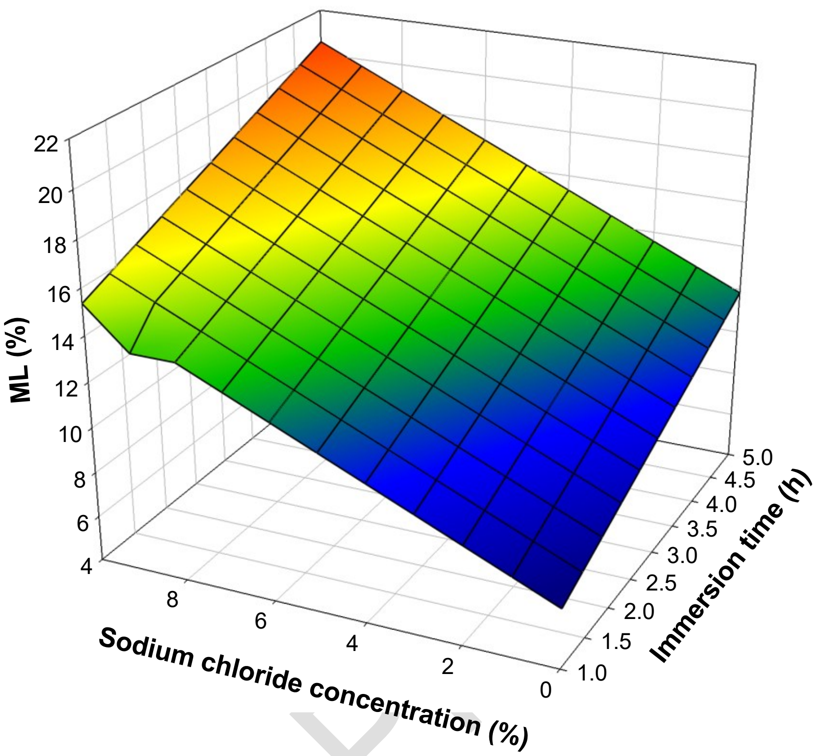
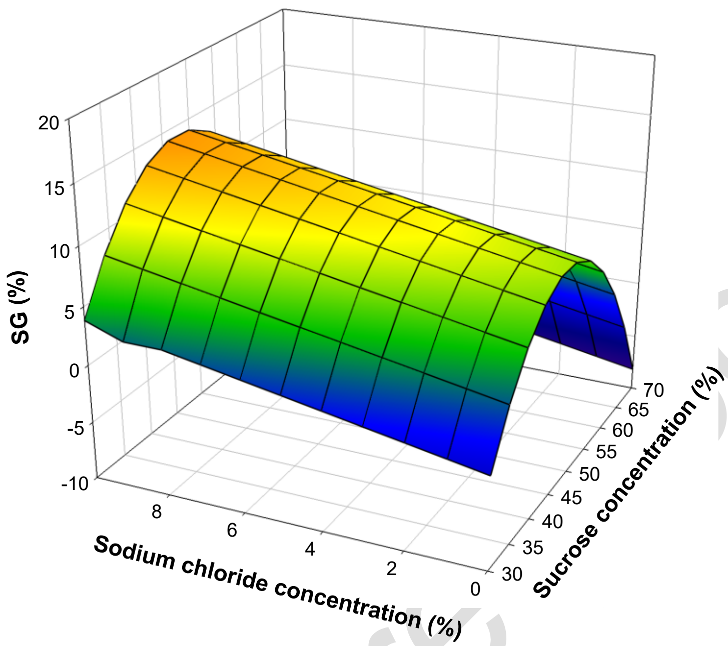
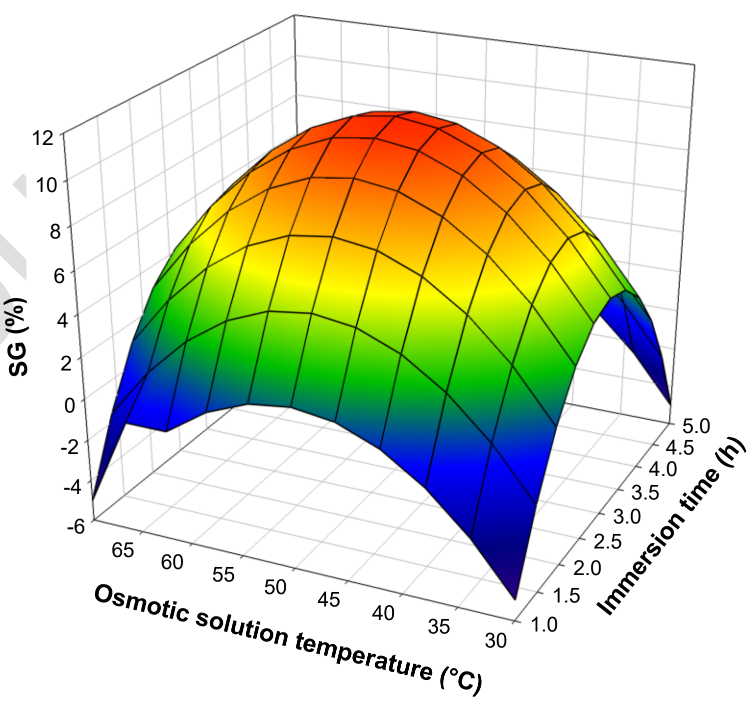


Fig. 2: Response surfaces for ML of fig fruits

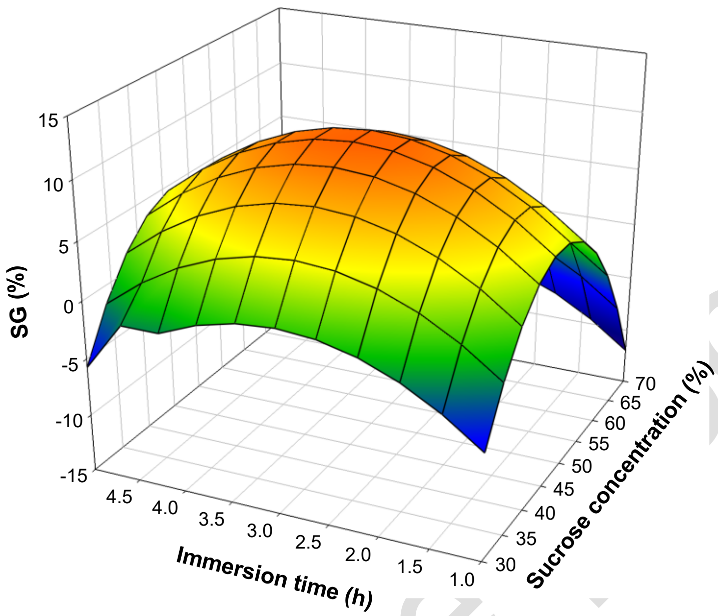
a)


SG (%)
20
15
10
5
0
-5
-10
8
6
4
2
0
Sodium chloride concentration (%)
30
35
40
45
50
55
60
65
70
Sucrose concentration (%)

b)


SG (%)
12
10
8
6
4
2
0
-2
-4
-6
65
60
55
50
45
40
35
30
Osmotic solution temperature (°C)
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Immersion time (h)

c)



d)

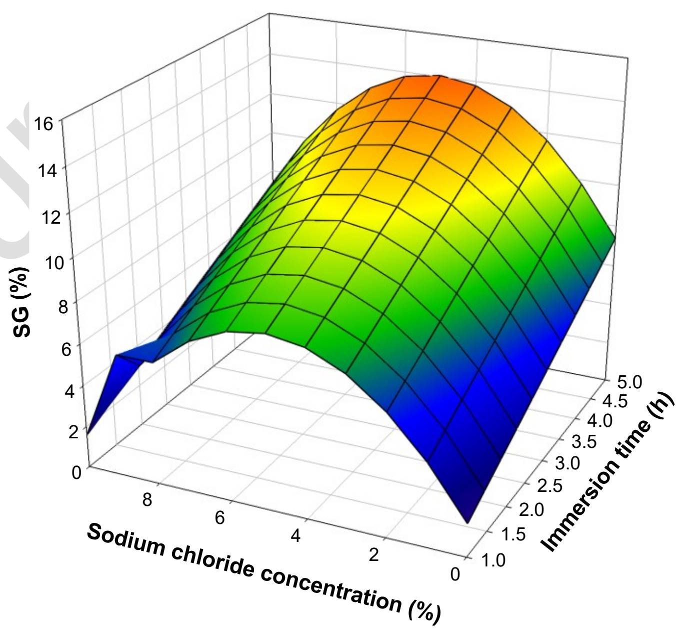


Fig. 3: Response surfaces for the SG of fig fruits

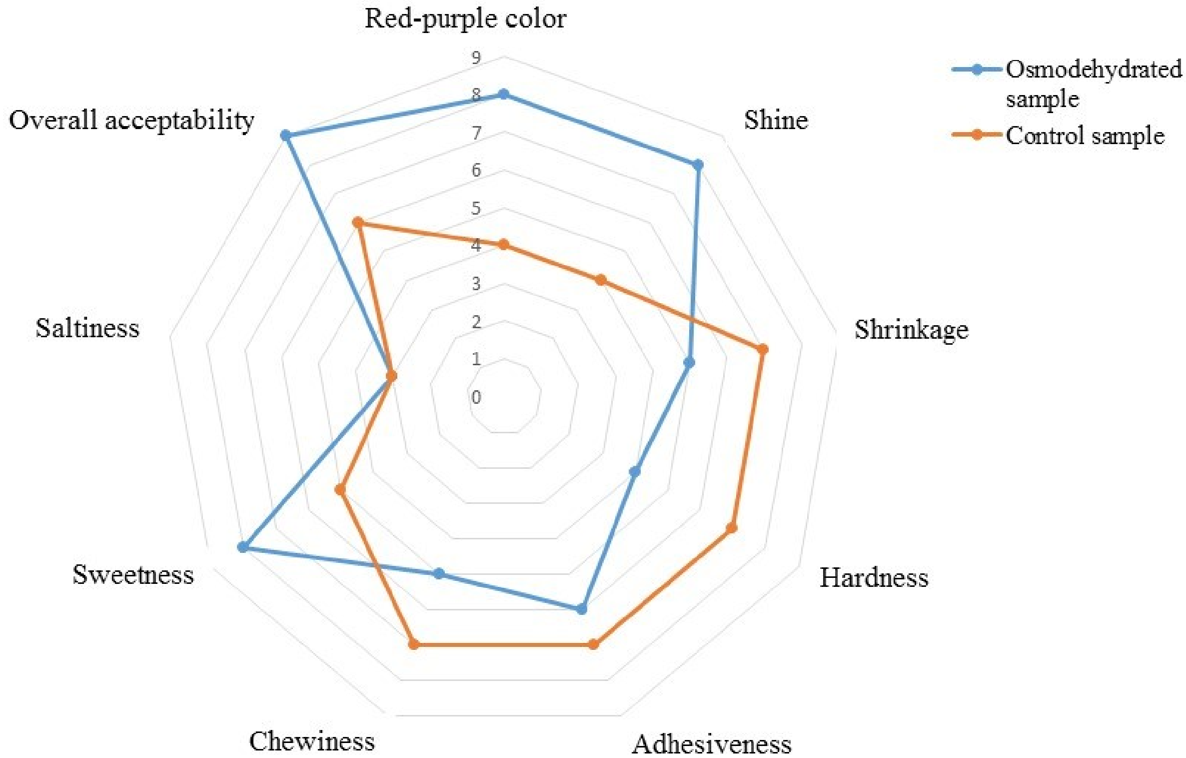


Fig 4. Sensory scores for the attributes on the hedonic scale (osmo-dehydrated sample at the optimum process condition and control sample). Average scores (scale 1-9) for red-purple color (axis 1), shine (axis 2), shrinkage (axis 3), hardness (axis 4), adhesiveness (axis 5), chewiness (axis 6), sweetness (axis 7), saltiness (axis 8) and overall acceptability (axis 9)

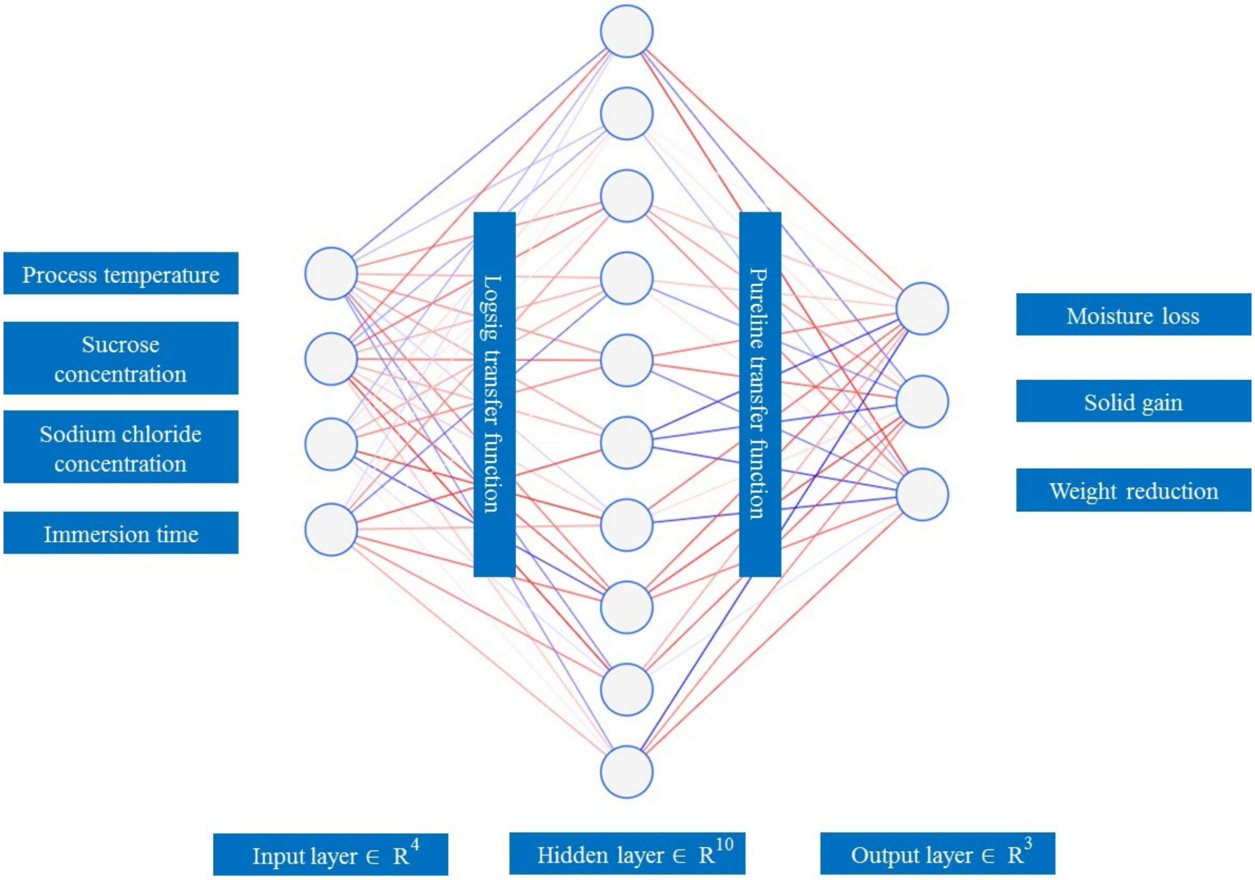
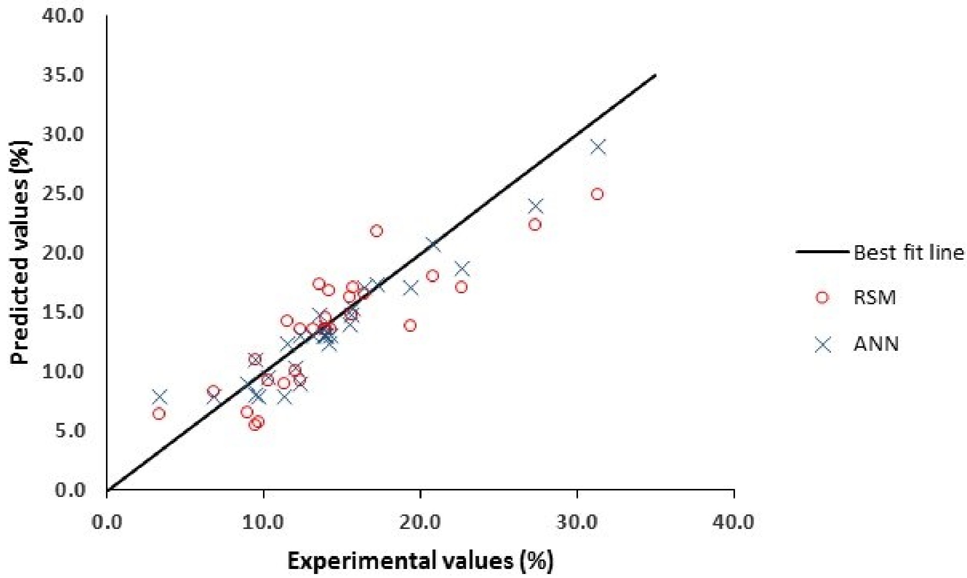


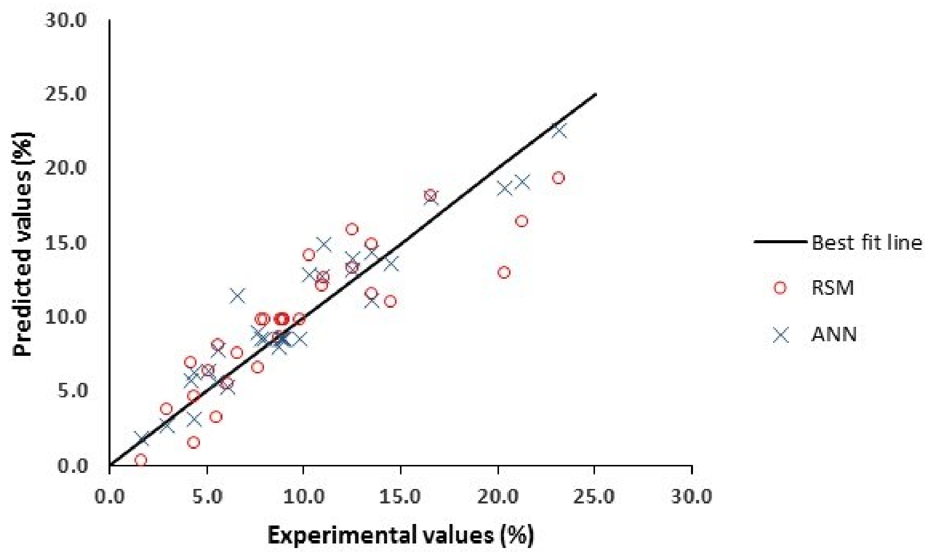
Fig. 5: Structure of multilayer feedforward neural network

a)



Predicted values (%)
Experimental values (%)
0.0
5.0
10.0
15.0
20.0
25.0
30.0
35.0
40.0
Best fit line
RSM
ANN

b)



Predicted values (%)
Experimental values (%)
0.0
5.0
10.0
15.0
20.0
25.0
30.0
Best fit line
RSM
ANN

c)

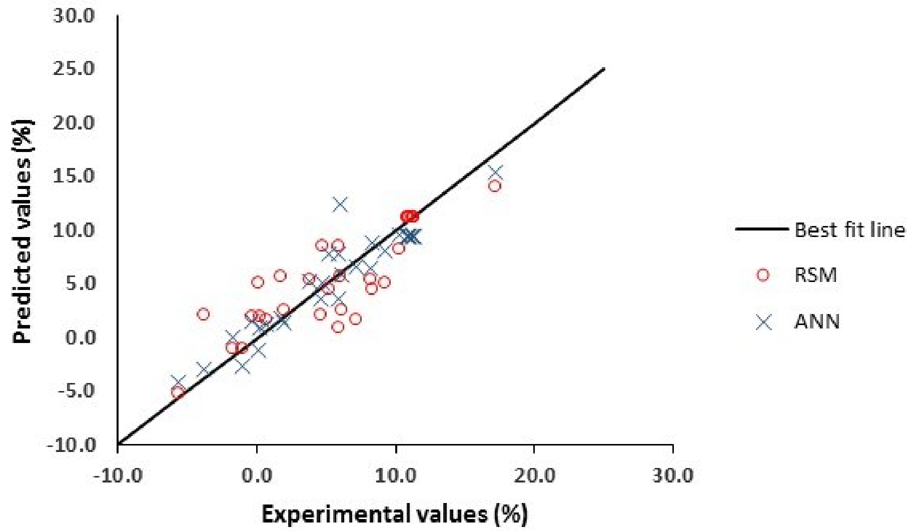


Fig. 6: Experimental vs. predicted values of RSM and ANN models for a) ML (%), b) WR (%) and c) SG (%).

Table 1: Error functions and the corresponding equations

Error function	Equation
Root mean square error	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_{i,e}-Y_{i,p})^2}{n}}$ (Eq. 9)
Mean absolute percentage error	$MAPE\ (\%) = \frac{100}{n}\sum_{i=1}^{n}\left\lvert\frac{Y_{i,e}-Y_{i,p}}{Y_{i,p}}\right\rvert$ (Eq. 10)
Correlation coefficients (R^2)	$R^2 = \frac{\sum_{i=1}^{n}(Y_{i,p}-Y_{i,e})}{\sum_{i=1}^{n}(Y_{i,p}-Y_{e})^2}$ (Eq. 11)

Table 2: ANOVA for the experimental results of CCRD

Source	ML (%)	WR (%)	SG (%)
Coefficients			
B_0	13.6***	8.74***	11.1***
Linear			
B_1	4.07***	4.16***	0.0449*
B_2	1.75**	2.17***	-1.55**
B_3	1.30*	1.45***	1.456**
B_4	2.18***	1.72***	0.780*
Quadratics			
B_{11}	0.115	0.766	-2.36***
B_{22}	0.235	0.205	-3.32***
B_{33}	-0.111	0.0523	0.092
B_{44}	0.658	0.0359	-1.664***
Interactions			
B_{12}	1.40	1.084*	1.756**
B_{13}	-0.214	-1.13*	0.606
B_{14}	-0.0271	0.0598	0.550
B_{23}	-1.08	-0.665	-0.0984
B_{24}	2.06**	0.939	0.484
B_{34}	-0.175	0.939	-1.60*
R^2	0.740	0.775	0.721
Adj R^2	0.688	0.740	0.651
Std Dev.	3.12	2.69	3.22
Regression			
DF	5	4	6
SS	693	649	642
MS	139	162	107
F	14.2	22.4	10.3
Significance of F	1.25E-06	4.14E-08	1.14E-05
Residual			
DF	25	26	24
SS	244	188	248
MS	9.76	7.24	10.4
Total			
DF	30	30	30
SS	937	837	891

***Highly significant (P<0.01), **Significant (P<0.05), *Critical limit (0.05<P<0.1)

Table 3. Optimization criteria for different independent variables (Temperature, sucrose concentration, sodium chloride concentration and immersion time) and responses (ML, WR and SG) for optimum conditions

Parameters	Desired goal	Lower limit	Upper limit	Importance	Solution
Temperature (ºC)	In range	30	60	3	60
Sucrose concentration (%)	In range	30	70	3	70
Sodium chloride concentration (%)	In range	0	5	3	5
Contact time (h)	In range	1	5	3	5
ML (%)	Maximize	5.46	25	5	24.10
WR (%)	Maximize	1.65	23.2	3	21.81
SG (%)	Minimize	-5.26	14.1	3	3.88

Table 4. Prediction performance of perceptron neural network for osmotic dehydration parameters of fig fruits

Dependent variables	Error functions	Number of Neurons				
		1	5	10	15	20
ML (%)	RMSE	0.679	0.597	0.522	0.531	0.512
	R^2	0.891	0.898	0.910	0.899	0.915
WR (%)	RMSE	0.554	0.514	0.497	0.489	0.512
	R^2	0.897	0.902	0.910	0.901	0.878
SG (%)	RMSE	0.678	0.621	0.554	0.613	0.576
	R^2	0.801	0.859	0.883	0.865	0.880

Table 5: Comparison between RSM and ANN models

Statistical parameters	ML (%)		WR (%)		SG (%)	
	RSM	ANN	RSM	ANN	RSM	ANN
Root mean square error	1.46	0.522	1.28	0.497	1.43	0.554
Mean absolute percentage error	0.181	0.138	0.231	0.165	2.69	0.584
Correlation coefficients (R^2)	0.740	0.910	0.775	0.910	0.725	0.883

Journal Pre-proofs

چکیده

آب‌گیری اسمزی میوه‌های انجیر در محلول سه‌تایی آب، ساکارز و کلرید سدیم در غلظت‌های مختلف محلول، دما و زمان‌های غوطه‌وری مختلف فرآیند مورد بررسی قرار گرفت. یک رویکرد مقایسه ای بین شبکه عصبی مصنوعی (ANN) و روش سطح پاسخ (RSM) برای پیش‌بینی پارامترهای انتقال جرم انجام شد. نتایج نشان داد که تمامی متغیرهای مستقل به طور مثبت وزن را کاهش دادند به این معنی که افزایش هر یک از عوامل منجر به افزایش کاهش وزن شد و این رابطه خطی بود. انجیرهای خشک شده به روش اسمزی کیفیت بهتری نسبت به نمونه های بدون اسمز داشتند. هر چهار متغیر مستقل ۹۴ درصد کاهش وزن، ۹۰ درصد کاهش رطوبت و ۸۹ درصد افزایش جامد را شرح دادند. شرایط بهینه فرآوری دمای ۶۰ درجه سانتی گراد، غلظت ساکارز ۷۰ درصد، غلظت کلرید سدیم ۵ درصد و زمان غوطه وری ۵ ساعت بود. نتایج نشان داد که مدل ANN که به درستی آموزش داده شده است در مقایسه با مدل RSM پیش‌بینی دقیق‌تری را انجام می دهد.

واژگان کلیدی: انجیر (*Ficus carica*)، خشک‌کردن اسمزی، شبکه‌های عصبی مصنوعی، روش سطح پاسخ، کاهش رطوبت، جذب ماده جامد